Designing and measuring environmental indicators for adverse maternal health outcomes.

Authors (Proposed)

Prestige Tatenda Makanga[1¶]; Liberty Makacha[1;2¶]; Reason Mlambo[1¶]; Newton Nyapwere[1¶]; Yolisa Prudence Dube[1¶]; Rachel Craik[2]; Hiten Misty[2]; Laura A. Magee[2]; Benjamin Barrat[3]; Peter von Dadelszen[2;4], on behalf of the **PRECISE Network**[^]

Author affiliations

[1] Place Alert Labs, Department of Surveying and Geomatics, Faculty of Science and Technology, Midlands State University, Gweru, Zimbabwe.

[2] Department of Women and Children's Health, School of Life Course Sciences, Faculty of Life Sciences and Medicine, King's College London, London, UK.

[3] Environmental Research Group, School of Public Health, Imperial College London, London, UK.

[4] Department of Obstetrics and Gynecology, University of British Columbia, Vancouver, Canada

Notes on Authorship

¶ These authors contributed equally to this work.

^ Membership of the CLIP Study Group is provided in S1 Table.

Corresponding Author:

Liberty Makacha
Senga Road
P Bag 9055
Gweru
Zimbabwe
Tel: +263 (0)778 814336
Email: makachal@staff.msu.ac.zw

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OBJECTIVES

- To illustrate optimal ways of measuring geographically varying phenomena that elevate the risk of adverse maternal health outcomes related to placental function.

- To develop and measure indicators for physical and socio-geographical factors that are related to placental disorders.

KEY POINTS

- We can't blanket understandings around the characterisation of socio-geographic exposures as there is a geography to these exposures
- We seek to challenge dominant clinical perspectives in public health intervention approaches through the introduction of a geographical perspective to key determinants of health

KEYWORDS
Spatial data, spatial analysis, Health research, GIS

Abstract

INTRODUCTION

GLOBAL MATERNAL HEALTH AND ITS DETERMINANTS

Action on the determinants of health is a key global health priority including maternal health (1–3). Interventions that target these distal pathways to negative outcomes for pregnant women and their babies have generally received less attention compared those clinical in nature. However, these nonclinical factors that affect pregnancy outcomes are many and affect different pregnancy outcomes in different ways. These determinants are a function of the woman's exposure to different characteristics of her environment.

Many epidemiological studies have suggested associations between environmental exposures and adverse maternal health outcomes. However, most of these studies have focussed on the physical environment in isolation. In this study we adopt a broad perspective to what constitutes the environment to encompass both the physical as well as social characteristics around the pregnant woman. The known environmental exposures attributed to disparities in maternal health outcomes exist both at individual as well as at community level and are a function of geography (4).

Physical environmental risk factors implicated in negative pregnancy outcomes include exposure to heavy metals, air quality, flood proneness and spatial access to care. These factors are usually experienced at the community level and vary across different geographies. Prenatal exposure to heavy metals such as lead, mercury and cadmium is one of the strongest known risk factors for preeclampsia (5). Heavy metals are highly implicated in inducing placental disfunction which commonly results in hypertensive disorders (6–8), affecting both the pregnant woman and the foetus – since the placenta is the nexus between the two. Air quality, in particular passive smoke from tobacco as well as household air pollution from use of solid fuels, has also been associated with preeclampsia, still births and low birth weight (9–11). A retrospective cohort study by (12) revealed significant positive correlations between physical isolation and flood proneness to adverse maternal health outcomes in Mozambique. This was also confirmed in studies by (13) and (14) who investigated the effect of seasonal variation of spatial access to care on maternal health outcomes due to flooding.

Concerning the social environment, individual-level social risk factors known to elevate adverse pregnancy outcomes include antenatal care seeking behaviour, autonomy (15), social inclusion, and religion. Two aspects of autonomy are identified in the literature as being important determinants of maternal health i.e., decision-making power on maternal health issues and on household finances. High autonomy among pregnant women both at the individual and community level has generally been shown to positively influence antenatal care-seeking behaviour (16,17), which in turn is protective against adverse pregnancy outcomes. In addition, there are other individual-level socio-demographic factors that have been identified to be associated with pregnancy outcomes, including parity, marital status, maternal education, type of maternal employment and religion.

While there is consensus on the contribution of both faucets of the environment to pregnancy outcomes, the development of appropriate frameworks for modelling and measuring the said environmental factors has not been adequately explored and is not yet part of mainstream thinking in global health policy. This presents a serious limitation on generating evidence and creating targeted interventions that counter the impact of the environment on pregnancy outcomes.

GEOGRAPHY, GIS AND GLOBAL MATERNAL HEALTH

The Geo-Information Sciences largely emerged from need in the environmental sciences. Initially this was for measuring and managing phenomena that was physically geographical, including forest management in the vast and not-so-easy to reach regions of Canada. GIS has grown to include capabilities for quantifying socio-geographical characteristics of places including characterization of social contexts and how these have an effect on maternal and other health outcomes (4,18,19).

The geospatial sciences present a unique opportunity for measuring aspects of a woman's environment that may contribute to risk for adverse pregnancy outcomes, including her physical and social environments. Geography and GIS are implicit in 2 global health priorities that influence strategies for improving maternal health. The emphasis on eliciting local perspectives on the determinants of health is a new priority (3) that will elucidate how place and geographical context (the differences that a place makes) shapes maternal health outcomes. The emphasis on monitoring determinants and health outcomes at more disaggregate spatial levels to better target interventions (3) has presented new opportunities to further take advantage of GIS for this.

While the opportunities for adopting a geographic perspective and using tools like GIS to understand and take action on the determinants of health are immediately apparent, there has been less effort to illustrate how these can be measured, particularly to an audience that will typically take action on these. In this article we build on a previous scoping review (20) to illustrate and design methods of measuring geographical indicators that can be used to represent environmental exposures related to placental disorders. These will serve as a guideline for empirical work in public health to enhance understandings of key determinants of health as well as guiding policymaking, illuminating crucial entry points for interventions and policy planning.

- Small area analyses vs large scale analyses

Methods

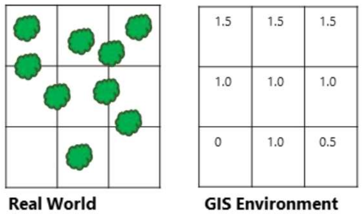
This work was premised with a scoping review on the interactions between social and environmental exposures with outcomes related to placental disorders (20). The articles from the review were revisited to understand the geographic mechanisms behind how these determinants occurred.

This was followed by a rapid review of the literature to identify how these mechanisms have been quantified in other application in GIS. For the indicators that required new approaches to modelling, we developed new methods using spatial analysis functions in GIS that appropriately mimic the geographical issue under question. We sought to develop indicators that would measure physical geographical characteristics, and as well illustrate how to use geography as an organizing principle for some of the socio-geographical indicators.

The data for the indicators were generally presented either as vector or raster format, depending on the nature of the phenomenon to be represented (21). The vector data model presents spatial elements as points, lines and polygons whilst raster model presents data in grids or pixels(21,22). Raster data type is best for the representation of continuous data like temperature and from sources such as aerial photographs, satellite imagery while vector is best for discrete data like village points and roads (23).

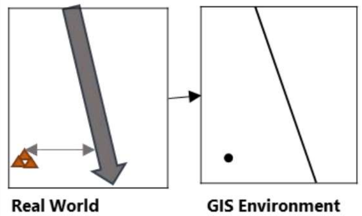
Results

1a. NDVI



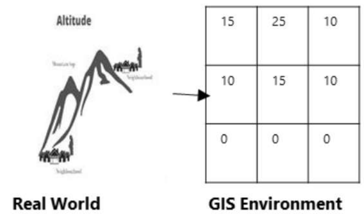
Normalised difference vegetation index (NDVI) with health wellbeing as a proxy measure for air quality. High NDVI values is inversely proportional to air pollution levels

1b. Euclidian Distance



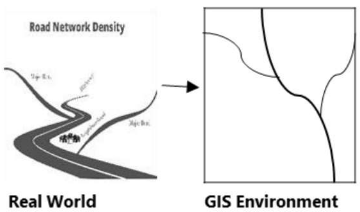
Euclidean distance to major roads is a proxy for traffic pollution which is spatially non-linear, with the highest levels adjacent to roads and a non-linear decay with increasing distance.

1c. Altitude



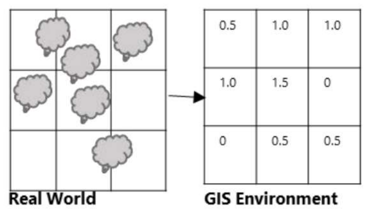
Atmospheric pressure and air circulation changes by elevation could affect movements of air pollutants and air pollution concentrations at a given location.

1d. Road Network Density



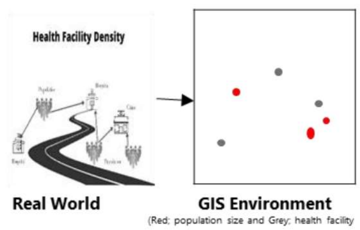
Road related pollution increases with an increase in road density, the population living near busy roads such as highways and major roads are more likely to be affected by vehicular pollution. It is calculated as a function of road length and area.

1e. Quasi-direct Air Quality Measures



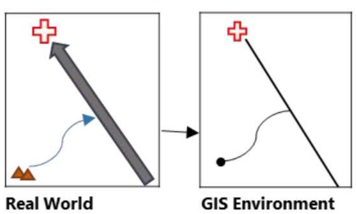
These measures include $PM_{2.5}$, NO_2, PM_{10}, $PM_{2.5\ No\ Dust}$ and SO_2 and can be calculated from satellite images as estimates for air pollution exposures.

2a. Health Facility Density



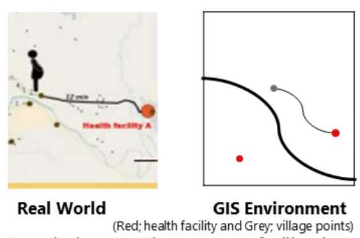
Health facility density reflects the total number of health centres relative to population size.

2b. Road Quality Index



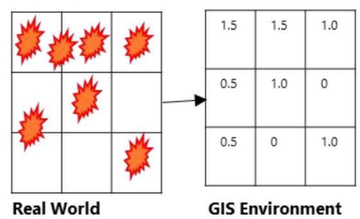
The quality of roads used to transport women to health facilities differ with the type of the road and seasonal variations. It is calculated as a function of road length and speed limit.

2c. Spatial Access to Care



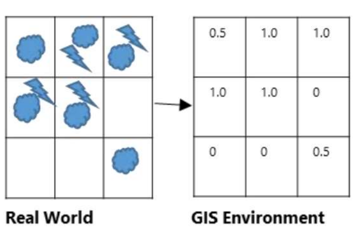
Travel time to the nearest facility is a known determinant of access to care. Delays in getting to a health facility when there is a pregnancy related need is the second of three delays known to elevate risks for adverse maternal outcomes

3. Temperature



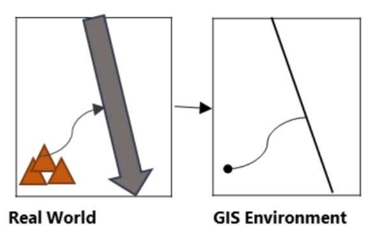
Birth weight and length have seasonal fluctuations due to temperature variations. This is calculated from sentinel images as average, maximum and minimum monthly temperature.

4. Precipitation



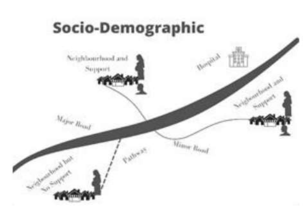
Birth weight and length may also have seasonal fluctuations due to precipitation variations.

5. Isolation



Walking distance to major roads is a proxy for isolation indicator. The longer the walking, the more isolated a place where the woman live is. Isolation is calculated as a function of population and distance to major roads.

6. Socio-Demographic



Include processes by which societies combat poverty and social exclusion, communities and families provide support, nutrition and partner employment status, education level, availability, support as well as violence tendencies

Indicator	Measures	Datasets	Approach/Design
1. Air Quality	a) Normalised Difference Vegetation Index (NDVI)	Landcover – satellite Landsat images(30m) alternative source at 10m resolution can be downloaded from Sentinel 2a	Previous research has shown correlation between satellite derived vegetation indices such as normalised difference vegetation index (NDVI) with health wellbeing as a proxy measure for air quality (24–26). This index is computed by determining the reflectance values in the visible red (RED) and near-infrared (NIR) bands of remotely sensed images. High NDVI values are inversely proportional to air pollution levels. These values can be calculated per village as follows averaging the pixel values of the NDVI raster within each village boundary.
	b) Euclidian Distance to Highways	Road dataset, pregnant women population data	Euclidean distance to road is a proxy for traffic pollution (27,28). The concentration of traffic pollutants is spatially non-linear, with the highest levels adjacent to roads and a non-linear decay with increasing distance. b) ∑ (Population ∗distance to nearest highway)/∑Population c) ∑ (Population ∗distance to nearest major road)/∑Population
	c) Euclidian Distance to Major Roads	Road dataset, pregnant women population data	
	d) Altitude	Digital Elevation Model (DEM), pregnant women population data	Atmospheric pressure and air circulation changes by elevation could affect movements of air pollutants and air pollution concentrations at a given location (29). For each village/Neighbourhood, mean elevation pixel value for each village is computed
	e) Quasi-direct Air Quality Measures i. $PM_{2.5}$ ii. NO_2 iii. PM_{10} iv. $PM_{2.5\ No\ Dust}$ v. SO_2	High Resolution satellite images	Satellite Images + Chemical Transport Modelling. Bayesian geostatistical regression (GR) models are capable of estimating air pollution exposures at high spatial resolutions. They can also quantify prediction uncertainties as well as providing probabilistic inference on the exceedance of air quality thresholds, though the approach comes with high computational burdens (30). Values for each raster are averaged per neighborhood
	f) Road Network Density	Road dataset, pregnant women population data	Road related pollution increases with an increase in road density as more roads built are in response of high traffic volume in an area motivated by social and economic benefits of these roads. Estimates of how pollution levels decay with distance to project the spatial distribution of road pollution have been determined before. The population living near busy roads such as highways and major roads are more likely to be affected by vehicular pollution. (31) f) ∑ (road length)/area;
2. ANC Seeking Behaviour	a) Health Facility Density	health facilities, pregnant women population density	Health facility density reflects the total number of health centres relative to population size. Health centre density helps measure physical access to health care services. (32) Comprised of two sub measures, number of facilities per 1000 pregnancies and weighted average facility level (proxy for accessible maternal healthcare services). Facility density/1000 pregnancies = (no. of facilities/no. of pregnancies) x 1000. Facility weight = facility level x Number of pregnancies. Average facility weight = facility weight/pregnancy density.

	b) Road Quality Index	Road dataset (dry and wet), pregnant women population density	The quality of roads used to transport women to health facilities differ with the type of the road and seasonal variations. Paved or unpaved roads affects the quality of the road which affects navigability. During the wet season, roads are usually flooded, and the quality of the roads is poor due flooding and slipper road surfaces. These limitations ultimately affect speed limit in each respective road surface. Travel times to seek healthcare in a road with low RQI are long and may have adverse effect health outcomes. (33) RQI= (∑ (road length x speed limit)/∑road length)/120km/h)	
	c) Spatial access (Travel time to the nearest health facility)	Road network, village point dataset, health facilities	Travel time to the nearest facility is a known determinant of access to care. Delays in getting to a health facility when there is a pregnancy related need is the second of three delays known to elevate risks for adverse maternal outcomes (34). Travel time can be calculated using network analysis and averaged per community	
3)Temperature	a) Mean Monthly Temperature	sentinel satellite images	Average monthly temperature for the month	Birth weight and length have seasonal fluctuations due to temperature variations (35,36)
	b) Max Monthly Temperature	sentinel satellite images	Maximum temperature in the month	
	c) Min Monthly Temperature	sentinel satellite images	Minimum temperature in the month	
	d) Temperature Variation	sentinel satellite images	Sum of Daily average temperature/Number of days in the month	
4) Precipitation	a) Mean Monthly precipitation b) Max Monthly precipitation c) Min Monthly precipitation	Precipitation Rasters	a) Average monthly precipitation for the month per community b) Maximum precipitation in the month per community c) Minimum precipitation in the month per community	Birth weight and length may also have seasonal fluctuations due to precipitation variations (36)
5) Isolation	a) Walking distance from the Village Centroid to the major road and walking distance to highway	Road network, village point dataset, population density	∑ (Population ∗walking distance to major roads)/∑Population; Walking distance to major roads is a proxy for isolation indicator. The longer the walking, the more isolated a place where the woman live is. (37)	
6) Socio-Demographic Indicators	a) Social Inclusion/Exclusion	Community surveillance, or census data. All census type data may be disaggregated to the spatial unit of interest (say community) and appropriate rates calculated for each measure.	Number of people participating in Healthy Communities Initiatives and activities and within 30min walking time to primary care. The process by which societies combat poverty and social exclusion	
	b) Community Help		Standardized individual score of community support by Village/Neighbourhood	
	c) Family Support Emotional		Family Support Scale (FSS)	
	d) Awareness of Strategies		Standardized total Level of awareness to Health practices by locality/neighbourhood	

	Employed in other communities		
	e) Decision autonomy (general and pregnancy related)		Standardized Mothers' Autonomy in Decision Making (MADM) scale by Village/Neighbourhood
	f) Financial Autonomy (general and pregnancy related)		Standardized Financial Autonomy in Decision Making (FADM) scale by Village/Neighbourhood
	g) Nutrition		Cultural beliefs in have been shown to affect women's diet and weight weight gain during pregnancy. Links between a woman's nutrition and pregnancy outcomes have also been studied. These influences may vary from place to place (38) (39) (40)
	h) Partner/household head education		Standardized total Level of education per each village/neighbourhood
	i) Partner/head employment status		Standardized total level of employment status for partner/head by village/neighbourhood Low education level results in partners/household head's inability to recognize warning signs requiring EmOC. Partners' lack of interest in 'females' issues (41)
	j) Partner/head availability		Standardized total level of availability for partner/head by village/neighbourhood In some cases, delays in seeking ANC were linked to the husband's financial constraints which increases the risk of adverse outcomes. Some male partners pointed out that if they were unemployed, they were unable to provide food for their pregnant wives. (41), (42)
	k) Partner support		Standardized total level of partner support by village/neighbourhood According to matrons and TBAs in Mozambique, although the husband was the primary decision-maker, in practice he was usually not around when complications occurred. (41)
	l) Partner violence tendencies		Standardized total level of partner violence tendency by village/neighbourhood Some partners do not help with child caretaking and domestic chores thereby elevating the risk of adverse maternal health outcomes. Men prioritizing pleasure (e.g., purchasing alcohol) over pregnancy wellbeing [Mozambique QR] (41)
	m) Extended family availability		Standardized total level of availability for extended family by village/neighbourhood Intimate partner violence was described as important factor affecting health and well-being in pregnancy. "...there are men who, when they beat pregnant women, do not look where they hit, and they can even hit in the belly. It can even be where the baby's head is, and the baby may be stillborn..." (42)

Include seasonal variation in indicators

Discussion and conclusion

New Opportunities

While this is not the first time that GIS is being used to create indicators that measure environmental matters that elevate risk, it presents the first systematic process for exhaustively documenting how these can be operationalized in a GIS environment. We present a guideline and resource for health researchers interested in studying these impacts.

Local Perspectives

Disaggregating data

Targeting interventions outside the clinic

References

1. Kelly MP, Bonnefoy J. The social determinants of health developing an evidence base for political action. NHS; 2007.

2. Marmot M, Friel S, Bell R, Houweling TAJ, Taylor S. Closing the gap in a generation: health equity through action on the social determinants of health. The Lancet. 2008;372(9650):1661–9.

3. UN General Assembly. Transforming our world: the 2030 Agenda for Sustainable Development. See Relat Glob Initiat Transnatl Organ Crime"Organized Crime Cross-Cut Threat Sustain Dev January 2015. 2015;

4. Makanga PT, Sacoor C, Schuurman N, Lee T, Vilanculo FC, Munguambe K, et al. Place-specific factors associated with adverse maternal and perinatal outcomes in Southern Mozambique: a retrospective cohort study. BMJ Open. 2019 Oct 17;9(2):e024042.

5. Kahn LG, Trasande L. Environmental Toxicant Exposure and Hypertensive Disorders of Pregnancy: Recent Findings. Curr Hypertens Rep. 2018;20(10):87.

6. Navas-Acien A, Guallar E, Silbergeld EK, Rothenberg SJ. Lead exposure and cardiovascular disease—a systematic review. Environ Health Perspect. 2007;115(3):472–82.

7. Roman HA, Walsh TL, Coull BA, Dewailly É, Guallar E, Hattis D, et al. Evaluation of the cardiovascular effects of methylmercury exposures: current evidence supports development of a dose--response function for regulatory benefits analysis. Environ Health Perspect. 2011;119(5):607–14.

8. Abhyankar LN, Jones MR, Guallar E, Navas-Acien A. Arsenic exposure and hypertension: a systematic review. Environ Health Perspect. 2012;120(4):494–500.

9. Owili PO, Muga MA, Kuo H-W. Gender Difference in the Association between Environmental Tobacco Smoke and Birth Weight in Africa. Vol. 15, International Journal of Environmental Research and Public Health . 2018.

10. Nieuwenhuijsen MJ, Dadvand P, Grellier J, Martinez D, Vrijheid M. Environmental risk factors of pregnancy outcomes: a summary of recent meta-analyses of epidemiological studies. Environ Health. 2013;12(1):6.

11. Pope DP, Mishra V, Thompson L, Siddiqui AR, Rehfuess EA, Weber M, et al. Risk of low birth weight and stillbirth associated with indoor air pollution from solid fuel use in developing countries. Epidemiol Rev. 2010;32(1):70–81.

12. Makanga PT, Sacoor C, Schuurman N, Lee T, Vilanculo FC, Munguambe K, et al. Place-specific factors associated with adverse maternal and perinatal outcomes in Southern Mozambique: a retrospective cohort study. BMJ Open. 2019 Feb 6;9(2).

13. Makanga PT, Schuurman N, Sacoor C, Boene HE, Vilanculo F, Vidler M, et al. Seasonal variation in geographical access to maternal health services in regions of southern Mozambique. Int J Health Geogr. 2017 Sep 15;16.

14. Firoz T, Vidler M, Makanga PT, Boene H, Chiaú R, Sevene E, et al. Community perspectives on the determinants of maternal health in rural southern Mozambique: a qualitative study. Reprod Health. 2016;13(Suppl 2):112.

15. Tiruneh FN, Chuang K-Y, Chuang Y-C. Women's autonomy and maternal healthcare service utilization in Ethiopia. BMC Health Serv Res. 2017;17(1):718.

16. Ononokpono DN, Odimegwu CO. Determinants of maternal health care utilization in Nigeria: a multilevel approach. Pan Afr Med J. 2014;17(Suppl 1).

17. Adjiwanou V, LeGrand T. Gender inequality and the use of maternal healthcare services in rural sub-Saharan Africa. Health Place. 2014;29:67–78.

18. Makanga PT, Sacoor C, Schuurman N, Lee T, Vilanculo FC, Munguambe K, et al. Place-specific factors associated with adverse maternal and perinatal outcomes in Southern Mozambique: a retrospective cohort study. BMJ Open. 2019 19;9(2):e024042.

19. Curtis S, Rees Jones I. Is There a Place for Geography in the Analysis of Health Inequality? Sociol Health Illn. 1998;20(5):645–72.

20. Dube YP, Nyapwere N, Magee LA, Vidler M, Moore SE, Barratt B, et al. Interactions between the Physical and Social Environments with Adverse Pregnancy Events Related to Placental Disorders—A Scoping Review. Int J Environ Res Public Health. 2020 Jan;17(15):5421.

21. Karnatak HC, Saran S, Bhatia K, Roy PS. Multicriteria Spatial Decision Analysis in Web GIS Environment. GeoInformatica. 2007 Sep 24;11(4):407–29.

22. Yao X, Li G. Big spatial vector data management: a review. Big Earth Data. 2018 Jan 2;2(1):108–29.

23. Goyal H, Sharma C, Joshi N. An Integrated Approach of GIS and Spatial Data Mining in Big Data. Int J Comput Appl. 2017 Jul 17;169(11):1–6.

24. Reza M, Kusuma C, Hernawati R, Darmawan S. CORRELATION ANALYSIS OF PM10 AIR POLLUTION WITH NDVI (NORMALIZED DIFFERENCE VEGETATION INDEX) BASED ON LANDSAT-8 AND SENTINEL-2A SATELLITE IMAGES Case Study : Bandung City , West Java. 2014;43–54.

25. Sedda L, Tatema AJ, Morley DW, Atkinson PM, Wardrop NA, Pezzulo C, et al. Poverty, health and satellite-derived vegetation indices: Their inter-spatial relationship in West Africa. Int Health. 2015;7(2):99–106.

26. Yang BY, Markevych I, Bloom MS, Heinrich J, Guo Y, Morawska L, et al. Community greenness, blood pressure, and hypertension in urban dwellers: The 33 Communities Chinese Health Study. Environ Int. 2019;126(November 2018):727–34.

27. Barnett AG, Plonka K, Seow WK, Wilson LA, Hansen C. Increased traffic exposure and negative birth outcomes: A prospective cohort in Australia. Environ Health Glob Access Sci Source. 2011;10(1):1–11.

28. Hitchins J, Morawska L, Wolff R, Gilbert D. Concentrations of submicrometre particles from vehicle emissions near a major road. Atmos Environ. 2000;34(1):51–9.

29. Eum Y, Song I, Kim H-C, Leem J-H, Kim S-Y. Computation of geographic variables for air pollution prediction models in South Korea. Environ Health Toxicol. 2015;30:e2015010–e2015010.

30. Beloconi A, Vounatsou P. Bayesian geostatistical modelling of high-resolution NO2 exposure in Europe combining data from monitors, satellites and chemical transport models. Environ Int. 2020 May;138:105578.

31. Phillips BB, Bullock JM, Osborne JL, Gaston KJ. Spatial extent of road pollution: A national analysis. Sci Total Environ. 2021;773:145589–145589.

32. https://improvingphc.org. Health center density (per 100,000 population) | PHCPI [Internet]. 2013. Available from: https://improvingphc.org/indicator/health-center-density-100000-population#?loc=&viz=0&ci=false

33. Gage AJ, Guirlène Calixte M. Effects of the physical accessibility of maternal health services on their use in rural Haiti. Popul Stud. 2006;60(3):271–88.

34. Makanga PT, Schuurman N, Sacoor C, Boene HE, Vilanculo F, Vidler M, et al. Seasonal variation in geographical access to maternal health services in regions of southern Mozambique. Int J Health Geogr. 2017 Jan 13;16(1):1.

35. Rylander C, Odland J øyvind, Sandanger TM. Climate change and the potential effects on maternal and pregnancy outcomes: An assessment of the most vulnerable - the mother, fetus, and newborn child. Glob Health Action. 2013;6(1):1–9.

36. Yu X, Feric Z, Cordero JF, Meeker JD, Alshawabkeh A. Potential influence of temperature and precipitation on preterm birth rate in Puerto Rico. Sci Rep. 2018;8(1):1–9.

37. Makanga PT, Sacoor C, Schuurman N, Lee T, Vilanculo FC, Munguambe K, et al. Place-specific factors associated with adverse maternal and perinatal outcomes in Southern Mozambique: a retrospective cohort study. BMJ Open. 2019 Feb;9(2):e024042.

38. Abubakari A, Jahn A. Maternal Dietary Patterns and Practices and Birth Weight in Northern Ghana. Ashton N, editor. PLOS ONE. 2016 Sep 9;11(9):e0162285.

39. Feresu SA, Harlow SD, Woelk GB. Risk Factors for Low Birthweight in Zimbabwean Women: A Secondary Data Analysis. Thorne C, editor. PLOS ONE. 2015 Jun 26;10(6):e0129705.

40. Girma S, Fikadu T, Agdew E, Haftu D, Gedamu G, Dewana Z, et al. Factors associated with low birthweight among newborns delivered at public health facilities of Nekemte town, West Ethiopia: a case control study. BMC Pregnancy Childbirth. 2019 Dec;19(1):220.

41. Munguambe K, Boene H, Vidler M, Bique C, Sawchuck D, Firoz T, et al. Barriers and facilitators to health care seeking behaviours in pregnancy in rural communities of southern Mozambique. Reprod Health. 2016 Jun;13(S1):31.

42. Tabassum, Firoz the CWG, Vidler M, Makanga PT, Boene H, Chiaú R, et al. Community perspectives on the determinants of maternal health in rural southern Mozambique: a qualitative study. Reprod Health. 2016 Sep;13(S2):112.