

The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 2026

Volume 41, Pages 149-165

ICRETS 2026: International Conference on Research in Engineering, Technology and Science

## **Geospatial Causal Inference for Barangay-Level Maternal Care Assessment: A Causal Forest Framework on Antenatal Intervention Outcomes in Davao City**

**Patrick Cerna**

Mapua Malayan Colleges Mindanao

**Raphael Mico Barrios**

Mapua Malayan Colleges Mindanao

**JC-Rey Cata-al**

Mapua Malayan Colleges Mindanao

**Human Walter Olo**

Mapua Malayan Colleges Mindanao

**Abstract:** Maternal mortality is a critical concern globally, particularly in rural and economically disadvantaged countries. In the Philippines, despite national and local interventions, the situation remains a critical concern due to the country's reported Maternal Mortality Rate. This study develops a geospatial causal inference framework to assess the effectiveness of maternal care programs in Davao City, particularly in the barangay level, providing insights into local variations in maternal health outcomes. Using the Routine Health Information System dataset covering from 2020 to 2024, the usage of Causal Forest estimates heterogeneous treatment effects of antenatal interventions, including prenatal care, anemia management, skilled birth attendance, and laboratory screenings. Furthermore, Spatial cross-validation and falsification tests are applied to address spatial autocorrelation and validate causal robustness. Additionally, results are visualized through an interactive dashboard, enabling clear identification of high and low-impact areas for targeted interventions. The integration of causal machine learning with geospatial analysis demonstrates the potential to uncover localized intervention effectiveness, optimizing maternal care resource allocation and strategic planning, as well as improving maternal health outcomes in Davao City.

**Keywords:** Maternal health, Causal forest, Geospatial analysis, Antenatal care, Heterogeneous treatment effects

### **Introduction**

Maternal health refers to the health of women during pregnancy, childbirth and the postnatal period (WHO, 2019). All three stages of pregnancy are critical so ensuring positive experiences at every stage is important for both maternal and newborn survival and well-being. Maternal health care and outcomes have improved globally over the recent decades, however maternal mortality remains alarmingly high, particularly in low- and middle-income countries. Maternal morbidity refers to those occurring during pregnancy, childbirth, or within the postpartum period. According to the World Health Organization, in 2020, there was a record of an estimated of 287,000 women died from pregnancy-related causes, many of which, could have been prevent with timely and appropriate healthcare. The leading causes of these maternal mortalities include direct causes such as severe bleeding, infections, high blood pressure during pregnancy, unsafe abortion, and obstructed labor (WHO, 2023).

---

- This is an Open Access article distributed under the terms of the Creative Commons Attribution-Noncommercial 4.0 Unported License, permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

© 2026 Published by ISRES Publishing: [www.isres.org](http://www.isres.org)

Maternal health care involves three stages, namely antenatal care (ANC), intrapartum care, and postnatal care (PNC). Antenatal care covers risk identification, prevention, and management of pregnancy-related conditions, and health education (WHO, 2016). Intrapartum care spans the onset of labor through delivery of the placenta, ensuring safe childbirth (Hutchison et al., 2025). Postnatal care extends for six to eight weeks after birth, covering maternal recovery and newborn care, which includes breastfeeding, immunizations, and mental health support (Lopez-Gonzalez & Kopparapu, 2022; UNICEF, 2025). These stages are often prone to failure, leading to poor maternal outcomes, where studies highlight diseases such as preeclampsia, intrauterine fetal demise (IUFD), and infections as leading causes of maternal morbidity and mortality (Amosco et al., 2019). These findings show the importance of early and effective interventions, and systematic maternal care programs.

In the Philippines, maternal health remains a major public health concern. Despite national programs like the Maternal, Neonatal, and Child Health and Nutrition (MNCHN) Strategy, which developed frameworks that promote access to antenatal, childbirth, and postnatal services, emphasizing measurable policy improvements and strengthening its health systems (Haakenstad et al., 2022; PMNCH), maternal mortality rates continue to challenge the health system of the country. The Philippine Statistics Authority (PSA) reports that the maternal mortality ratio (MMR) in the Philippines remains above the SDG 3 target of 70 per 100,000 live births, with significant disparities abetween urban and rural areas. According to Inquirer (2023), the PSA reported that there were 2,478 women who died from maternal causes in 2021, the MMR for that is 189.21 per 100,000 live births which is the third deadliest number of maternal mortalities next to 1951 and 1952. In Davao City, maternal health is still a multifaceted issue, particularly in inequalities in the quality and accessibility of maternal care across barangays. In 2021, the City Health Office (CHO) recorded 22 maternal mortalities, which were primarily caused by hemorrhage and eclampsia, both are preventable with timely and quality prenatal care (City Government of Davao, 2022).

A qualitative study conducted by Cagayan et al. (2022), in rural health units in Luzon revealed the systemic challenges faced by mothers in accessing maternal health services. The study reported the challenges that included long travel distances, lack of transportation, poor facility readiness, and intermittent availability of skilled health professionals. Many women also reported feeling disrespected or neglected during health visits, which discouraged regular check-ups and facility-based deliveries. These insights highlight the persistent socio-structural and accessibility barriers that limit the effectiveness of existing maternal health programs. The study also shows the importance of local health units providing maternal care, especially the need for capacity building, resource allocation, and localized decisions-making tools to better help rural communities.

In response to these recorded maternal mortalities, the CHO intensified their efforts through the Safe Motherhood Program, having multiple initiatives aimed at improving maternal health services. This program includes services such as 18 batches of consultive meetings for district health staff, District Facebook Pages for pregnant women to receive necessary prenatal updates and advocacy materials, a planned Safe Motherhood Hotline and, a mobile clinic services that aims to bring prenatal care, nutrition counseling, laboratory tests, and micronutrient supplementation directly to communities.

The barangay and district health centers currently provide prenatal services that include nutritional assessments via BMI, Tetanus-Diphtheria immunization, micronutrient supplementation specifically iron and folic acid, deworming, STI and laboratory testing, and gestational diabetes screening. Despite these efforts, a study by Matutino et al. (2024) revealed inconsistent perceptions of care quality among mothers in selected barangays, citing resource limitations, follow-up gaps, and variable patient experiences as ongoing challenges.

These disparities despite the current efforts emphasize the need for a data-driven approach to support evidence-based decision-making in maternal care. While these services are in place, there remains a gap in the ability to assess the effectiveness of maternal care interventions and identify areas that most need support. The absence of these tools makes it difficult to track the success of interventions across the Davao City barangays over time.

To address this, this study will begin with the collation of selected barangay-level data from Davao City's Routine Health Information System (RHIS). Although RHIS is an administrative dataset, in this study it is considered the primary dataset because it was obtained directly from the City Health Office (CHO) before any cleaning or processing. This step is data gathering of the relevant indicators of this study such as, antenatal care services, maternal outcomes, and interventions activities across the different health centers in Davao City. Consolidating these varied datasets into a structured and analyzable format, this study will be able to have a more granular analysis and make sure that both successful and underserved areas are properly captured.

To further support maternal healthcare decision-making, researchers have delved into data-driven methods. Using effective data acquisition and preprocessing are foundational for accurate epidemiological models. Related studies include an automated electronic health record (EHR) extraction (Lijovic et al., 2024), hybrid SEIR-neural models with external variables (Ziarelli et al., 2024), and wastewater-based surveillance (Meadows et al., 2025) illustrate how innovative data sources improve health forecasting. Furthermore, Geospatial analysis provides powerful tools to identify health disparities. Studies in Africa and Asia used spatial clustering and Bayesian networks to map out maternal mortality ratios and neonatal outcomes, which reveal hotspots of regions of high maternal risk (Yaya et al., 2021; Rubaiya et al., 2024; Liu et al., 2024). Machine learning integrated with geospatial data further enables predictive mapping of maternal and child health disparities (Rajuroy & Emmanuel, 2025).

There are numerous machine learning models that were developed for maternal care. For instance, a hybrid model combining Random Forest and XGBoost identified significant predictors of antenatal care uptake (Sani & Ahmed, 2023), whereas other hybrid models such as MaternalNET-RF, which integrates Artificial Neural Networks and Random Forest, achieve performance metrics exceeding 94% (Togunwa et al., 2023). Ensemble approaches, including gradient-boosted trees and stacked models, outperform single algorithms in classification accuracy (Khadidos et al., 2024; Macrohon et al., 2022). Other ensemble methods such as bagging are also widely recognized for improving model robustness and reducing prediction variance (Breiman, 1996). Performance metrics such as accuracy, precision, recall, F1-Score and Area under the Receiver Operating Characteristic Curve (AUROC) were commonly used to evaluate these models, with hybrid methods achieving the best balance between sensitivity and specificity (Bertini et al., 2022; Sani & Ahmed, 2023). Despite these advances, most studies rely on small localized, datasets, producing population biases which limits their generalizability across diverse populations and overlooks the full continuum of maternal care. To mitigate these issues, oversampling methods such as Synthetic Minority Over-sampling Technique (SMOTE) are commonly applied, which helps to balance high-risk and low-risk cases (Elreedy & Atiya, 2019).

This study focuses on using Causal Forest, which is a machine learning method that focuses more on the identification of heterogeneous causal effects of treatment and is unlike the conventional machine learning methods (Kakimoto et al., 2022). In recent years, causal forests have been applied in various studies such as economics, transportation, and agriculture to make site-specific or context-specific decisions. A study by Kakimoto et al. (2022) utilizes the causal forest approach in the agricultural context, specifically to generate economically optimal site-specific input management recommendations based on the gathered on-farm experimentation data. Similarly, in the medical field, studies by Raghavan et al. (2022) and Susukida et al. (2025) utilizes causal forest to explore sugar control for diabetic patients and examine in psychology substance use disorder treatments respectively. Another study focuses on economics which their program provides individuals to meet their basic needs and escape poverty (Wu et al., 2023). These studies mentioned show the strength of causal forest in giving insights on how treatment effects vary across different population subgroups. This capability is relevant to this study's focus on barangay-level variation in maternal health outcomes.

Two methods were taken into consideration to tackle this study, and while Causal Forest was selected by the researchers due to it having a distinct ability to estimate Conditional Average Treatment Effects (CATEs) at a granular level, another method was also considered which is the Double Machine Learning (DML). DML is a statistically strong and effective way for estimating average treatment effects, but is it not designed to capture the heterogeneity of effects across diverse settings. In contrast, Causal Forest can reveal how maternal health interventions perform differently depending on barangay specific factors like access to facilities, resource allocation, and personnel distribution. A study by Zheng and Yin (2023) explained how Causal Forest is particularly well-suited for observational studies, because it enables nuanced, interpretable causal analysis. Furthermore, another study by Credit and Lehnert (2023) highlighted that Causal Forest is especially effective in spatially distributed datasets, where treatment impacts are uneven across the geography, this is an ideal choice for this study's target of health disparities within Davao City's 182 barangays. These strengths from this selected model align closely with the goal of the study which is to generate localized, actionable insights for maternal healthcare planning and policy.

To ensure the reliability of the hybrid model's output, the study also includes an evaluation phase using both cross-validation and falsification tests. In geospatial datasets such as maternal health indicators across barangays, using standard random cross-validation can lead to an overestimated model performance due to spatial autocorrelation, this is the tendency for neighboring areas to exhibit similar characteristics. To address this, this study applies spatial cross-validation, which partitions the data based on geographic blocks, making sure that the training and test sets are spatially independent. A study by Sun et al. (2023) emphasized the important role of Spatial Cross-Validation in GeoAI applications, also showing that the traditional Cross-Validation techniques can produce overly optimistic results in spatial domains. Along with the Cross-Validation strategy, falsification tests

will also be employed to evaluate the causal validity of the model. These tests detect potential confounding or misspecification by applying the model to outcomes that should not be influenced by maternal interventions, such as health indicators not related to maternal health. A study from Liu et al. (2023) highlighted that assumption-lean falsification tests are vital when deploying double-robust machine learning estimators in any observational settings, making sure of credible causal inferences by identifying the false positives that may arise from unobserved biases.

Together with the hybrid model, this study also integrates a web-based platform as a visualization layer rather than a core contribution. Built with React with Vite for the frontend and Flask for the backend, the system allows users to interact with heatmaps representing each barangay in Davao City. Color gradients to indicate the severity or effectiveness of the maternal health interventions will be shown on these heatmaps. This is done to enhance the accessibility and the interpretability of the study's results.

This study aims to address the gaps of maternal health care in the Davao City barangays with the help of causal forest and geographic heterogeneity. This study proposes a data-driven system that integrates routinely collected and selected health data and applies causal inference and geospatial analysis. With this combination of statistical modeling and spatial mapping the system will help the workers and policymakers of the health sector to see and understand which interventions work effectively, and in which barangays. These insights generated by the hybrid model will serve as a valuable tool for evidence-based planning for resource planning and targeted response in district to barangay-level maternal healthcare efforts. Specifically, this study aims to:

1. To construct a collated dataset by consolidating data on antenatal care services, maternal health outcomes, and interventions from the records of the Davao City Routine Health Information System (RHIS)
2. To train a hybrid model that applies Causal Forest algorithm to estimate how the effects of maternal health interventions vary across barangay-level subgroups and incorporate geospatial heterogeneity to visualize these heterogeneous treatment effects.
3. To evaluate the maternal care interventions hybrid model using Spatial Cross-Validation and Falsification Tests.

## Method

### Research Design

This study employs a quantitative, ecological research design aimed at assessing the causal relationship between maternal healthcare interventions and maternal and neonatal health outcomes across barangays in Davao City. The approach will integrate spatial analysis with the Causal Forest algorithm; to investigate how geographic factors influence the effectiveness of interventions such as prenatal care, skilled birth attendance, and maternal supplementation. This study will utilize observational health records and historical data from routine monitoring data instead of randomized control trials. This study will leverage natural variation in intervention intensity across barangays. The study applies causal inference techniques to estimate both Average and Conditional Average Treatment Effects (ATE and CATE). Geospatial data, health service records, and demographic features are all incorporated to reveal heterogeneity in outcomes. This chapter outlines the research setting, data sources, data preparation process, model implementation, validation techniques, and the visualization system that translates findings into actionable insights. The unit of analysis comprises aggregated data at the Barangay level. For indicators with sparse or unreliable data at the barangay level, the district level serves as the alternative unit of analysis.

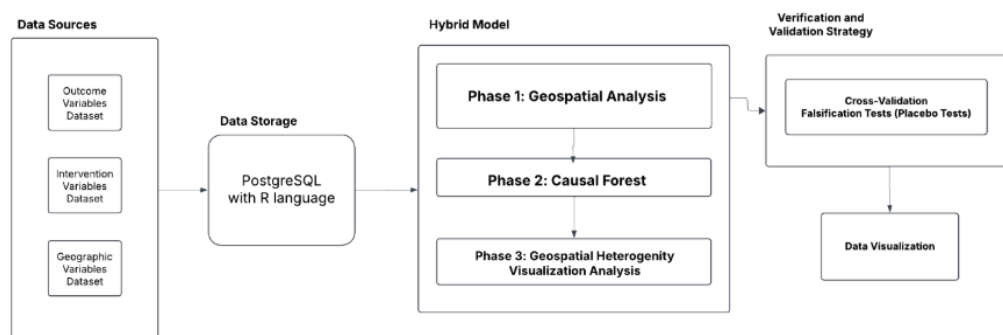


Figure 1. Conceptual framework

Figure 1 illustrates the overall conceptual framework of this study. It outlines the sequential and interconnected stages, beginning with the acquisition of primary and secondary data sources. These data then undergo rigorous processing and management, leading into a multi-phase analytical approach designed to investigate spatio-temporal trends in maternal health. The outputs of this analysis, including identified patterns and statistical models, culminate in the development of an interactive dashboard. Crucially, the framework emphasizes that verification and validation strategies are applied throughout the entire research process to ensure the credibility and utility of the findings.

### Research Setting and Time Frame

The research setting is Davao City, Davao Region, Philippines, encompassing the 182 barangays across 11 administrative districts. Due to availability of data, this study spans a five-year period from January 2020 to December 2024 utilizing historical data.

### Population and Locale

The study population does not use a fixed sample size. Instead, it is defined by the administrative boundaries of Davao City during the study period, with particular focus on women of reproductive age (15-49 years) and mothers/newborns represented in the maternal and child health (MCH) indicators. This encompasses all 182 barangays across the city's 11 districts.



Figure 2. Davao city districts

### Data Sources

This study utilizes primary routine health information system (RHIS) to ensure comprehensive analysis. The selection of multiple complementary data sources is essential to capture the multidimensional nature of maternal health outcomes and their determinants.

#### *Primary Data: Davao City RHIS*

This study uses the Davao City Routine Health Information System (RHIS) data. Although RHIS is an administrative dataset, in this study it is considered as the primary dataset because it is the direct source collected from CHO before any cleaning or processing. This serves as the foundation of this study for several critical reasons: (1) It provides the most comprehensive, systematically collected data on maternal health services and

outcomes in Davao City. (2) It offers granular geographic detail (barangay-level). (3) It contains longitudinal data allowing variation in exposures of maternal health interventions. (4) It represents the actual operational data used by health administrators for decision-making, ensuring research-to-practice relevance. The study relies on obtaining aggregated reports based on the standardized 2025 RHIS covering the period 2020-2024, obtained from the Davao City Health Office (CHO) through formal data sharing agreements.

## Key Datasets

These are the key datasets that were identified as integral parts of the analysis. They contain the most relevant indicators to identify the disparities in maternal health outcomes. Below are specific descriptions for each dataset describing the way these datasets are structured. These datasets are presented in a data dictionary to ease readability.

### Outcome Variables Datasets

The primary outcome dataset contains maternal and neonatal health outcomes and indicators at the barangay level. This dataset provides the dependent variables necessary for causal inference. The stillbirth dataset missing specific causes is a key limitation, however, analysis is still possible to identify its association with interventions. Stillbirth counts will be used as an outcome variable in the causal forest analysis. However, due to the lack of cause-specific information, interpretation will be limited to overall associations between interventions and stillbirth prevalence, rather than causal pathways of specific conditions. For specific causes of morbidity/mortality the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) will be used to identify the diagnosed cause of morbidity or mortality.

Table 2. Neonatal morbidity/mortality dataset

| Barangay   | Sex    | Cause Diagnosed | Age Group       | Neonatal Cases |
|------------|--------|-----------------|-----------------|----------------|
| Barangay A | Male   | A34             | 0 – 6 days      | 35             |
| Barangay B | Female | O00-O95         | 7 – 28 days     | 160            |
| Barangay C | Male   | O98-O99         | 7 – 28 days ... | 127 ...        |

*Note.* Barangay refers as the Geographic Unit. Sex is classified as “Male or Female”. Cause\_Diagnosed refers to the ICD-10 coded causes specifically on morbidity/mortality. Age\_Group refers to the count between ‘0-6 days’ and ‘7-28 days’. Neonatal\_Cases refers to the count of neonatal morbidity or mortality cases.

Table 3. Maternal morbidity/mortality dataset

| Barangay   | Age Group | Cause Diagnosed | Maternal Cases |
|------------|-----------|-----------------|----------------|
| Barangay A | <20       | A34             | 35             |
| Barangay B | 20 - 34   | O00-O95         | 160            |
| Barangay C | ≥35       | O98-O99         | 127            |

*Note.* Barangay refers as the Geographic Unit. Age\_Group refers to the defined reproductive age brackets. Cause\_Diagnosed refers to the ICD-10 coded causes of morbidity/mortality. Maternal\_Cases refers to the count of maternal cases.

Table 4. Stillbirth dataset

| Barangay   | Stillbirth Count |
|------------|------------------|
| Barangay A | 74               |
| Barangay B | 256              |
| Barangay C | 182              |

*Note.* Barangay refers to the Geographic unit. Stillbirth\_Count refers to the count of stillbirths.

### Intervention Variables Datasets

These datasets capture the implementation intensity of maternal healthcare interventions across barangays. These provide the treatment variables for causal analysis. The natural variation in implementation intensity across barangays creates the necessary treatment variation for causal identification. The variation is primarily caused by the practical limitations of implementing interventions due to resources allocation, infrastructure and community engagement.

Table 5. Prenatal care coverage dataset

| Barangay   | Prenatal_Visits | Birth_Plan |
|------------|-----------------|------------|
| Barangay A | 132             | 75         |
| Barangay B | 634             | 344        |
| Barangay C | 243             | 180        |

*Note.* Barangay refers to the Geographic unit. Prenatal\_Visits refers to the count of pregnant women completing recommended prenatal visits. Birth\_Plan refers to the count of pregnant women who received counseling on preparing birth plans.

Table 6. Maternal vaccination and supplementation dataset

| Barangay   | Vaccination_Rate | Supplementation_Rate |
|------------|------------------|----------------------|
| Barangay A | 274              | 287                  |
| Barangay B | 104              | 404                  |
| Barangay C | 468              | 269                  |

*Note.* Barangay refers to the Geographic unit. Vaccination\_Rate refers to the count of women who received Tetanus Vaccine. Supplementation\_Rate refers to the count of women administered iodine and iron supplements.

Table 7. Birth attendant and delivery location dataset

| Barangay   | Facility_Delivery_Rate | Skilled_Attendant_Rate | Home_Delivery_Rate |
|------------|------------------------|------------------------|--------------------|
| Barangay A | 201                    | 192                    | 9                  |
| Barangay B | 237                    | 48                     | 168                |
| Barangay C | 273                    | 269                    | 4                  |

*Note.* Barangay refers to the Geographic unit. Facility\_Delivery\_Rate refers to the count of births in health facilities. Skilled\_Attendant\_Rate refers to the count of births attended by skilled birth attendants. Home\_Delivery\_Rate refers to the count of births at home.

Table 8. Screening and diagnostic coverage dataset

| Barangay   | Lab_Exams_Coverage | CBC | Stool | Urinalyses | Screening_Coverage |
|------------|--------------------|-----|-------|------------|--------------------|
| Barangay A | 431                | 151 | 86    | 108        | 86                 |
| Barangay B | 496                | 124 | 74    | 99         | 199                |
| Barangay C | 549                | 220 | 55    | 165        | 109                |

*Note.* Barangay refers to the geographic unit. Lab\_Exams\_Coverage refers to the count of pregnant women who received the required laboratory tests. CBC, Stool, and Urinalyses refer to the number of conducted tests on pregnant women and correspond to the dataset variables “Lab\_Exams\_CBC, Lab\_Exams\_Stool, and Lab\_Exams\_Urinalyses” respectively. Screening Coverage refers to the count of pregnant women screened for key maternal health conditions.

## Data Processing and Management

The study implements a systematic data processing workflow designed to transform raw administrative data into analysis-ready datasets while preserving data integrity and maximizing information extraction.

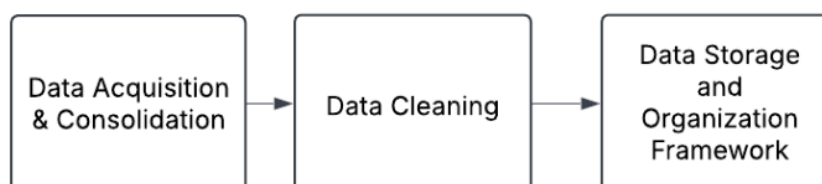


Figure 3. Data processing and management plan

### Data Acquisition & Consolidation

The nature of the data requires extensive selection and removal of irrelevant data points. The RHIS dataset is a large and comprehensive report on all public health related data. There is a large amount of data within the dataset that serves no purpose to the thesis as our focus is on maternal health. The maternal health care dataset from RHIS is represented by nineteen Excel files for each of Davao City's districts. Within these files contain individual

sheets for every month of the year and all the relevant maternal health statistics subdivided into individual barangays. With five years of data from 2020-2024, there is a total of ninety-five individual Excel files. These files were created primarily to optimize data entry and readability. This results in structural issues that make it difficult to work with. Specifically, merged header cells, multiple header rows, embedded formatting, and references to external files. Steps need to be taken in order to manage these structural issues to ensure efficient data management.

There are 298 data rows in the excel file; however, most of these are subsets of other statistics that are divided by age-group or other subdivisions. There are also a significant number of rows that contain data that is irrelevant to study. These will need to be managed accordingly so that only relevant data is collected. The relevant data will be selected and transferred to a comprehensive database with all relevant data cleaned and ready for further analysis. These will then be compiled into more specific datasets to be implemented into causal forests.

A standardized script will be used to integrate the Excel files into R; the script includes importing the Excel files and managing the different sheets within them. Following that, the script will remove irrelevant formatting and fix column and row names. This step is essential for integrating data from disparate sources with different structures. Creating structured integration protocols ensures consistent merging methodology across temporal and spatial dimensions. These protocols include standardized naming conventions, assigning unique identifiers to barangays/districts, and ensuring the handling of different levels of granularity.

### *Data Cleaning*

The RHIS dataset is already a comprehensive and aggregated report that is submitted to the national government as such. However, because it is primarily formatted for reporting instead of analysis, extensive formatting adjustments are required. However, due to RHIS being primarily a reporting system for decision makers, there is substantial formatting and redundant rows and columns for the sole purpose of readability and data entry. Before data cleaning when the Excel file is imported into R, there is a total of ~400 columns, most of these are just artifacts from the way it was formatted and presented in Excel.

These formatting artifacts will need to be carefully removed and excluded from the dataset. Column headers for each barangay are repeated multiple times within the dataset. There are multiple merged cells and entries that provide additional information to the data. Empty placeholder columns for each barangay that are used for data entry. The rows that exist solely to aggregate statistics that were divided by group such as age group, pregnancy trimester, or screened and diagnosed patients. After removing all the formatting data and data entry columns, the resulting data set now only has 298 rows and the correct number of columns for barangays that exist within each district.

### *Data Storage and Organization Framework*

The aggregated dataset will then be stored to PostgreSQL, providing flexible data queries and seamless integration to the dashboard for data visualization. Data security and access control will remain under the discretion of the CHO.

### **Data Analysis**

The analysis will be conducted in three sequential phases using robust statistical and computational methods. Each analytical method has been carefully selected based on its suitability for addressing specific research questions, handling the characteristics of maternal health data, and specifically, for identifying heterogeneous treatment effects in a spatial context. The overarching goal is to transform processed data into actionable insights regarding intervention effectiveness across Davao City.

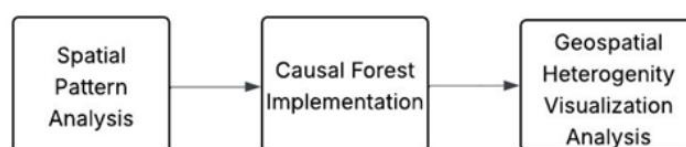


Figure 4. Data analysis plan

### *Phase 1: Spatial Pattern Analysis*

This initial phase focuses on characterizing the spatial distribution of key variables and identifying underlying geographic patterns that may influence both intervention implementation and health outcomes. This allows for a deeper understanding of the research setting and informs the subsequent causal inference models.

#### A) Geographic Feature Engineering

This step involves creating new spatial variables that encapsulate critical aspects of access and infrastructure.

**Healthcare Worker-to-Population Ratios:** For each barangay, calculate the ratio of different types of healthcare personnel (e.g., doctors, nurses, midwives, Barangay Health Workers) to its total population.

#### B) Facility Density and Distribution Metrics

**Spatial Density:** The number of birthing facilities per Barangay.

**Categorization of Facilities:** Facilities will be categorized and their distributions analyzed to understand the types of services available within different geographic areas.

**Spatial Clustering:** This involves identifying areas with statistically significant concentrations of similar characteristics, which could indicate underlying spatial processes or disparities.

### *Phase 2: Causal Forest Implementation*

This phase is the core of causal inference, leveraging the strengths of Causal Forests to estimate the heterogeneous impacts of interventions. Causal Forests are particularly suited for this study due to their ability to (1) handle high-dimensional data with numerous covariates without requiring strong assumptions about their functional forms, (2) robustly estimate causal effects in the presence of complex confounding, and most importantly, (3) directly estimate heterogeneous treatment effects (HTE), allowing for the identification of how intervention effectiveness varies across different barangays based on their unique characteristics. This machine learning approach provides a non-parametric way to uncover nuanced causal relationships that traditional linear models might miss. The model specifications are as follows:

#### A) Outcomes (Y):

- Maternal morbidity/mortality rates
- Neonatal mortality/morbidity rates
- Stillbirth rates

#### B) Treatments (W):

- Prenatal care coverage metrics
- Maternal vaccination rates
- Maternal supplementation rates
- Skilled birth attendant delivery rates
- Health facility delivery rates
- Screening and diagnostic test coverage rates

Below are the intervention variables, representing the "intensity" or coverage of maternal healthcare interventions within each barangay. Each intervention will be analyzed individually as a "treatment" variable against the outcomes.

#### C) Covariates (X):

- Demographic characteristics: Age distribution of birthing mothers, barangay population density, total barangay population.

- Facility access and geographic features: The engineered variables from Phase 1, including healthcare worker-to-population ratios, facility density, and barangay spatial categories. These are crucial for understanding geographic heterogeneity.
- Temporal indicators: Year and month fixed effects to account for time trends or seasonality in health data.

Furthermore, the following are the potential confounders and effect modifiers that influence both intervention uptake and health outcomes and are critical for achieving causal identification.

#### A) Causal Forest Training:

The Causal Forest model will be trained using the `grf` package in R (or `econml.grf` in Python), which implements Generalized Random Forests. This involves growing an ensemble of causal trees, where each tree is built by recursively partitioning the covariate space to minimize the variance of treatment effect estimates within each leaf node.

#### B) Hyperparameter Tuning:

Key hyperparameters such as the number of trees (`num.trees`), minimum node size (`min.node.size`), and subsampling rates (`sample.fraction`) will be tuned using cross-validation to optimize model performance and ensure robust estimation.

#### C) Treatment Effect Estimation:

- Average Treatment Effects (ATE): For each intervention, the overall average causal impact on the various maternal and neonatal health outcomes across all barangays will be estimated. This provides a general understanding of the intervention's efficacy.
- Conditional Average Treatment Effects (CATE): This is the primary output of interest for addressing the study's core question on heterogeneity. Causal Forests will estimate the CATE for each intervention at the individual barangay level, conditional on its unique profile of covariates (including all geographic features). This allows for a granular understanding of how the impact of a specific intervention varies from one barangay to another.
- Heterogeneous Treatment Effects across Geographic Features: The estimated CATEs will then be analyzed to explicitly identify how the effectiveness of interventions differs based on specific geographic features. This analysis will highlight which geographic contexts are most receptive or resistant to interventions.

### *Phase 3: Geospatial Heterogeneity Visualization Analysis*

This delves into understanding the drivers of the heterogeneous treatment effects identified in the Causal Forest Model, focusing heavily on geographic factors.

#### A) Variable Importance Measures:

- Quantifying Predictive Power: The importance of each geographic feature in explaining the variation in estimated treatment effects will be formally assessed. This will be done by examining how much each covariate contributes to the heterogeneity in the estimated CATEs within the Causal Forest framework (e.g., using "feature importance" metrics specifically designed for HTE estimation in causal forests, which identify variables that predict differences in treatment effects).
- Comparison of Spatial vs. Non-Spatial Variables: A direct comparison will be made to ascertain whether spatial variables are more predictive of treatment effect variation than traditional demographic or socio-economic variables. This will highlight the unique contribution of the spatial dimension to understanding intervention effectiveness.

#### B) Interaction Analysis:

- Identifying Thresholds and Synergies: While causal forests implicitly account for complex interactions, this phase will explicitly analyze key interactions to provide actionable insights. This includes:

- **Role of Facility Type and Personnel Allocation:** Investigating if specific types of facilities or higher allocations of particular healthcare personnel amplify or diminish the effects of certain interventions, especially in remote or underserved areas.

### **Verification and Validation Strategy**

Rigorous verification and validation strategies will be employed throughout the analysis to ensure the robustness, reliability, and generalizability of the study's findings, particularly concerning the causal claims in a spatial context.

#### **A) Cross-Validation**

- **Spatial Cross-Validation:** To accurately assess the model's performance and avoid overfitting due to spatial autocorrelation, blocked cross-validation will be implemented. This approach ensures that training and validation sets are geographically independent, providing a more conservative and realistic estimate of predictive accuracy and causal effect estimation.
- **Out-of-Sample Prediction Evaluation:** The performance of the causal forest models will be evaluated on unseen data using appropriate metrics. For continuous outcomes (rates), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) will be used. For binary outcomes or proportions, Area Under the Receiver Operating Characteristic Curve (AUC), precision, recall, and F1-score will be considered. The stability of estimated CATEs across different cross-validation folds will also be monitored.

#### **B) Falsification Tests (Placebo Tests):**

- **Applying Methodology to Unaffected Outcomes:** The causal forest methodology will be applied to outcomes that are theoretically unlikely to be affected by the maternal healthcare interventions (e.g., adult male mortality rates, incidence of non-maternal/neonatal specific communicable diseases that do not directly involve the maternal health system). If significant causal effects are detected for these "placebo" outcomes, it would indicate potential unobserved confounding or issues with the causal identification strategy.
- **Testing for Effects Before Intervention Implementation:** Where historical data allows, the methodology will be applied to data from a period before the substantial implementation of the interventions being studied. The absence of significant "treatment effects" during this pre-intervention period would provide stronger evidence that the observed effects are genuinely attributable to the interventions rather than pre-existing trends or unobserved factors.

### **Ethical Considerations**

The study adheres to the highest ethical standards in health research, prioritizing data privacy, confidentiality, and responsible dissemination of findings. All data handling complied with the Data Privacy Act of 2012, ensuring confidentiality of patient records and ethical use of health information (Official Gazette, 2012).

- A) **Data Aggregation and De-identification:** The study will exclusively use aggregated, de-identified data at the barangay level. No individual patient information will be accessed, processed, or stored at any point. This ensures that the privacy of individuals is fully protected.
- B) **Formal Data Sharing Agreements:** A formal, Data Sharing Agreement (DSA) will be established with the Davao City Health Office (CHO). This agreement will explicitly outline the terms of data access, usage, storage, retention, and destruction, ensuring compliance with the CHO's data governance policies and national data privacy laws.
- C) **Responsible Reporting and Dissemination:** Research findings will be reported responsibly, focusing on public health implications and avoiding any form of stigmatization of specific geographic areas or populations. Results will be presented in a way that is culturally sensitive and promotes equitable health interventions. Complete findings, including the developed dashboard, will be shared proactively with the Davao City Health Office and other relevant public health stakeholders to inform evidence-based public health action and policy development.

### **Software and Tools**

The analysis will primarily utilize powerful open-source programming languages and specialized libraries, complemented by Geographic Information System (GIS) software and robust data management tools.

- Programming Languages:
- Python 3.9+:

Data Manipulation: Pandas 1.4.0+ for efficient data cleaning, transformation, and aggregation.

Geospatial Analysis: GeoPandas 0.10.0+ for working with spatial dataframes, performing spatial joins, and manipulating geographic features.

Statistical Modeling: Statsmodels 0.13.0+ for complementary statistical tests and basic regression analysis.

Visualization: Matplotlib, Seaborn, and Plotly for creating static and interactive data visualizations to present the analysis results.

API Routing: Flask framework and Cross-Origin Resource Sharing (CORS) to route requests to and from the frontend framework.

- R 4.1.0+:

Data Processing: tidyverse suite (e.g., dplyr, ggplot2, tidyr) for efficient data manipulation, visualization, and consistent syntax.

Causal Inference: grf (Generalized Random Forests) package for robust implementation of Causal Forests and other causal machine learning methods.

- GIS Software:
- QGIS 3.22+: A free and open-source desktop GIS application for advanced geospatial processing, digitizing, geocoding health facility addresses, creating detailed basemaps, performing network analysis for distance calculations and cartographic production for thesis figures.
- Database:
- PostgreSQL: This will serve as the primary database to hold the aggregated dataset to fetch data to the dashboard.

## Data Visualization



Figure 5. Davao City Barangays and Districts Shapefiles exported via GeoJSON from QGIS

Like other related studies, the best way to comprehend data is visualization through heatmaps by creating a dashboard. The dashboard consists of a map panel that only shows Davao City as well as its surrounding districts and barangays via GeoJSON shapefiles exported from QGIS, as well as card panels to display number statistics

of the dataset. The dataset, "philippines-psgc-shapefiles" by altcoder found on Github, is used for the shapefiles to trace out barangays found in Davao City, whereas OpenStreetMaps via overpass-turbo is used for tracing districts. This method saves performance on the app as the GeoJSON files are saved locally, rather than relying on APIs to fetch maps and shapefiles. In an administrative level to classify a country, barangays are classified as level 4, whereas districts are classified as level 2.

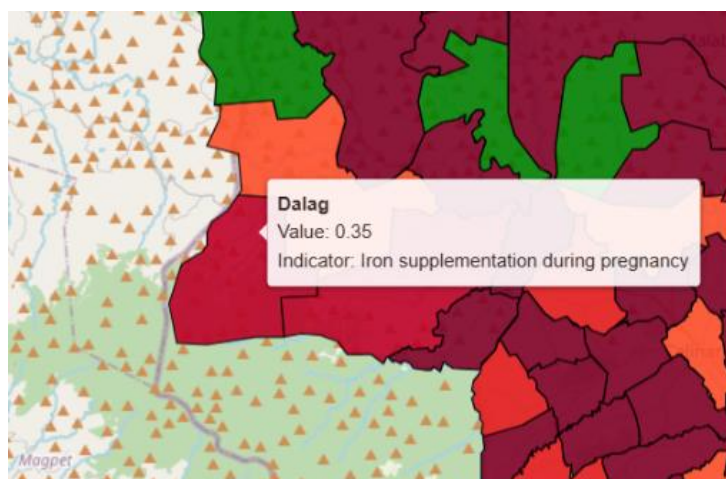


Figure 6. Sample Barangay heatmap with top indicator and value

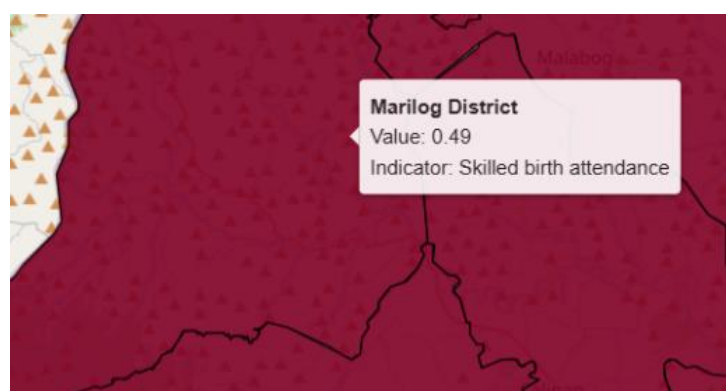


Figure 7. Sample district heatmap with top indicator and value

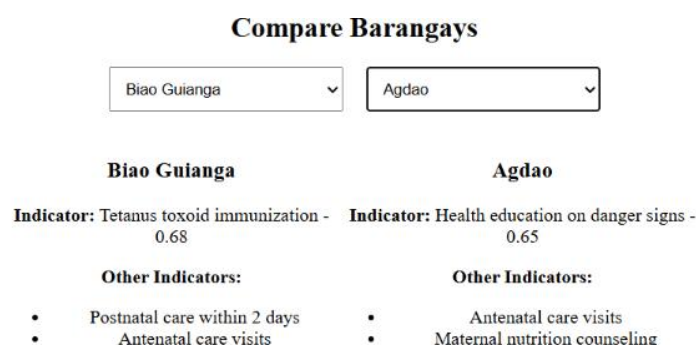


Figure 8. Comparing Barangay A and B

The frontend will be developed using JavaScript with the React framework under Vite, providing a lightweight and fast development environment. The backend will be powered by Python using the Flask framework, which is responsible for serving the GeoJSON shapefiles, handling API requests to fetch and process relevant data (e.g., maternal care indicators, barangay and district names, numerical data) and building the proposed model. These data values are bound to geographic units and visualized as color gradients on the map using heatmaps, allowing users to visually identify areas of concern or interest. Interactive features such as showing either barangays or districts on the map panel, as well as a component for comparing barangay A and B, will be implemented to enhance user engagement and support decision-making. Cards displayed on the right side of the map panel will provide an overview of the dataset, including numbers of total morbidity and mortality cases, along with other

relevant numerical indicators. The data presented in the figures above are for illustrative purposes only and do not represent the actual dataset to be used in the study.

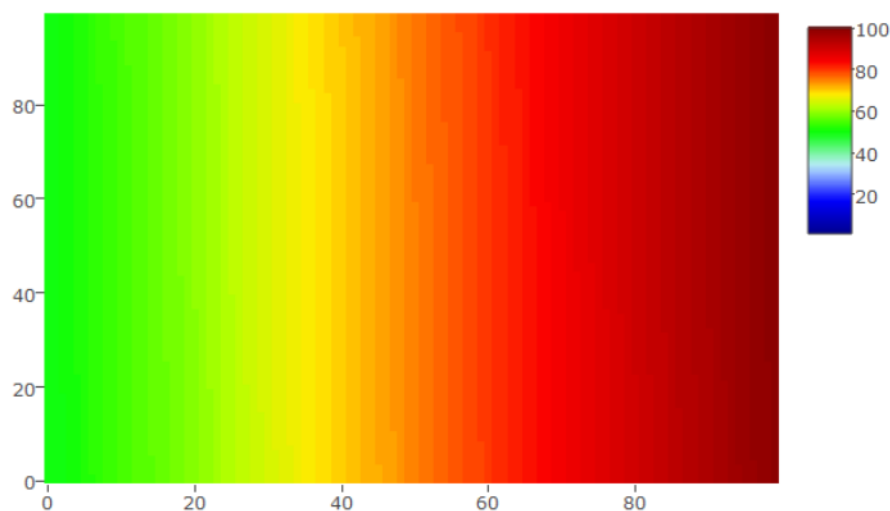


Figure 9. Sample green-to-red heatmap

The heatmaps will indicate the severity of predicted indicators based on the trained model. Each barangay will display the value of its top indicator, as well as other indicators based on its hierarchical value in descending order, and be classified as Safe (green), Caution (yellow), or Act (red).

## Results and Discussion

This study analyzed 10,920 barangay-month records from January 2020 to December 2024, covering 182 barangays in Davao City. The primary outcome of interest is the pregnancy outcome, measured as a normalized ratio of stillbirths/abortions to live births. The treatments evaluated are a comprehensive suite of maternal health interventions, including prenatal checkups, anemia and tetanus management, counseling, birth planning, screening for diseases, and ensuring skilled attendance at facility-based deliveries. A causal forest model was utilized with district-level blocked spatial cross-validation to estimate the causal effects of these interventions while accounting for geographic dependencies. As these results are preliminary, further model refinement will be necessary to precisely identify the relevance of specific covariates in driving treatment effect heterogeneity.

### *Preliminary Analysis: Causal Impact of Outcomes*

As a preliminary step before assessing the primary outcome, the causal forest was first applied to measure the effect of the interventions on key intermediate outcomes related to service utilization. This initial analysis is crucial for understanding *how* the program achieves its goals. The Average Treatment Effect (ATE) was estimated for various indicators, representing the intervention-driven increase in the probability of a pregnant woman receiving a specific service. The results show the interventions are highly effective in promoting foundational and planning-related aspects of prenatal care. The strongest causal impact was observed in the creation of birth plans (ATE: 0.301), followed by encouraging first-trimester prenatal visits (ATE: 0.234) and providing health information on danger signals (ATE: 0.216). These findings suggest the program successfully influences proactive health-seeking behaviors. Moderate effectiveness was observed in anemia management and supplementation protocols. The interventions led to a significant increase in the identification of anemic women among those tested (ATE: 0.186) and in the completion of iron with folic acid supplementation by the time of delivery (ATE: 0.127).

The program's impact on the uptake of specific laboratory screenings and tests was positive but more modest. Ensuring women receive three basic laboratory exams (ATE: 0.103) and hemoglobin determination (ATE: 0.092) were the most notable effects in this category. Conversely, screenings for specific diseases like Syphilis (ATE: 0.005), HIV (ATE: 0.004), and Hepatitis B (ATE: 0.001) showed the smallest causal impacts. A summary of these preliminary ATEs on service uptake is presented below.

Table 1. Average treatment effects (ATE)

| Category          | Indicator                                  | ATE   |
|-------------------|--------------------------------------------|-------|
| Prenatal Care     | No. of pregnant women with birth plan      | 0.301 |
|                   | First prenatal visit (1st PNV)             | 2.34  |
|                   | Provided with health info, advice, counsel | 0.216 |
| Anemia Management | Diagnosed with anemia                      | 0.186 |
|                   | Completed dose of iron with folic acid     | 0.127 |
| Screening/Testing | With three (3) basic laboratory exams      | 0.103 |
|                   | Hemoglobin determination                   | 0.092 |
|                   | Screened for gestational diabetes          | 0.046 |
|                   | Screened for Syphilis                      | 0.005 |

## Conclusion

This study demonstrates the successful application of a geospatial causal forest framework to evaluate a complex set of maternal health interventions in Davao City. By analyzing their impact on service uptake as a preliminary step, this research provides a nuanced understanding of the mechanisms through which the program operates. The initial findings are highly relevant for our primary stakeholder, the Davao City Health Office. The results indicate that current interventions are exceptionally effective at improving process-oriented outcomes like birth planning, early-trimester checkups, and health counseling. These are critical successes. However, the more modest impact on specific disease screenings suggests that targeted strategies may be needed to overcome barriers related to these services, which could include supply-side constraints, provider training, or patient-level factors.

As this research is ongoing, these preliminary results on service utilization form the foundation for the next phase of analysis. Future work will directly link the uptake of these specific services to the primary outcome—the reduction of stillbirths and abortions. By estimating the heterogeneous treatment effects, we will identify which interventions, in which specific barangays, have the greatest causal impact on saving lives. This will ultimately provide the Davao City Health Office with a data-driven tool to optimize resource allocation, refine public health strategies, and advance the goal of ensuring safe and healthy pregnancy outcomes for every mother in the city.

## Recommendations

To evaluate robustness across various methodological frameworks, future research should expand on this work by further honing the use of causal forests with alternative techniques like Bayesian causal inference and Double Machine Learning. An additional approach would be to broaden the analysis's scope to include other Philippine regions or comparable low- and middle-income country contexts. This would improve the findings' generalizability and offer comparative insights into the spatial heterogeneity of maternal health outcomes.

Researchers are also encouraged to incorporate individual-level datasets to complement barangay-level analyses and to allow deeper understanding of patient-level risk factors. Longitudinal validation with updated Routine Health Information System (RHIS) data is recommended to evaluate the temporal stability of treatment effects and to capture evolving patterns in maternal health care delivery. Moreover, integrating additional determinants such as socioeconomic indicators, transportation access, and cultural practices into causal frameworks may improve contextual interpretation. Lastly, future studies may explore the development of open-source, user-friendly geospatial decision-making support tools that extends beyond visualization to real-time predictive modeling, thereby proceeding its translational value of causal machine learning in maternal health research.

## Scientific Ethics Declaration

\* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

## Conflict of Interest

\* The authors declare that they have no conflicts of interest

## Funding

\* This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

## Acknowledgements or Notes

\* This article was presented as an oral presentation at the International Conference on Research in Engineering, Technology and Science ([www.icrets.net](http://www.icrets.net)) held in Batumi/Georgia on July 09-12, 2026.

## References

- Amosco, M. D., Tavera, G. R., Villar, V. A. M., Naniong, J. M. A., David-Bustamante, L. M. G., Williams, S. M., ... Palmes-Saloma, C. P. (2019). Non-additive effects of ACVR2A in preeclampsia in a Philippine population. *BMC Pregnancy and Childbirth*, 19(1), 11.
- Bertini, A., Salas, R., Chabert, S., Sobrevia, L., & Pardo, F. (2022). Using machine learning to predict complications in pregnancy: A systematic review. *Frontiers in Bioengineering and Biotechnology*, 9, 780389.
- Breiman, L. (1996). Bagging predictors. *Machine Learning*, 24(2), 123–140.
- Cagayan, M. S. F. S., Nisperos, G. A., Facun, G. G., Cagayan, B. S. S., Castro, M. C. R., & Silverio, C. E. (2022). Mothers' perspectives on utilization of maternal health services in rural health units in Luzon: A qualitative study. *Acta Medica Philippina*, 56(16), 56–63.
- City Government of Davao. (2022, May 25). *CHO intensifies safe motherhood program as Davao City logs 22 maternal deaths*. Retrieved from <https://www.davaocity.gov.ph/social-services/cho-intensifies-safe-motherhood-program-as-davao-city-logs-22-maternal-deaths/>
- Credit, K., & Lehnert, M. (2023). A structured comparison of causal machine learning methods to assess heterogeneous treatment effects in spatial data. *Journal of Geographical Systems*, 26(4), 483–510.
- Elreedy, D., & Atiya, A. F. (2019). A comprehensive analysis of synthetic minority oversampling technique (SMOTE) for handling class imbalance. *Information Sciences*, 505, 32–64.
- Haakenstad, A., Yearwood, J. A., Fullman, N., Bintz, C., Bienhoff, K., Weaver, M. R., ... Lozano, R. (2022). Assessing performance of the Healthcare Access and Quality Index, overall and by select age groups, for 204 countries and territories, 1990–2019: A systematic analysis from the Global Burden of Disease Study 2019. *The Lancet Global Health*, 10(12), e1715–e1743.
- Hutchison, J., Mahdy, H., Jenkins, S. M., & Hutchison, J. (2025). Normal labor: Physiology, evaluation, and management. In *StatPearls*. Treasure Island, FL: StatPearls Publishing.
- Inquirer, P. D. (2023, April 10). Philippines' maternal mortality rate worse than reported. *INQUIRER.net*. Retrieved from <https://opinion.inquirer.net/162254/philippines-maternal-mortality-rate-worse-than-reported>
- Kakimoto, S., Mieno, T., Tanaka, T. S. T., & Bullock, D. S. (2022). Causal forest approach for site-specific input management via on-farm precision experimentation. *Computers and Electronics in Agriculture*, 199, 107164.
- Khadidos, A. O., Saleem, F., Selvarajan, S., Ullah, Z., & Khadidos, A. O. (2024). Ensemble machine learning framework for predicting maternal health risk during pregnancy. *Scientific Reports*, 14(1), 21483.
- Lijović, L., de Grooth, H. J., Thorat, P., Bos, L., Feng, Z., Radočaj, T., & Elbers, P. (2024). Preparing for future pandemics: Automated intensive care electronic health record data extraction to accelerate clinical insights. *Journal of Intensive Medicine*, 5(2), 167–175.
- Liu, L., Mukherjee, R., & Robins, J. M. (2023). Assumption-lean falsification tests of rate double-robustness of double-machine-learning estimators. *Journal of Econometrics*, 240(2), 105500.
- Liu, T., Liu, J., & Cheng, T. C. F. (2024). Heterogeneity in the effect of green financing constraints on labor investment efficiency: A causal forest approach. *Economic Modelling*, 143, 106977.
- Lopez-Gonzalez, D. M., & Koppapapu, A. K. (2022). Postpartum care of the new mother. In *StatPearls*. Treasure Island, FL: StatPearls Publishing.
- Macrohon, J., Villavicencio, C., Inbaraj, X., & Jeng, J. (2022). A semi-supervised machine learning approach in predicting high-risk pregnancies in the Philippines. *Diagnostics*, 12(11), 2782.
- Matutino, R. I. K. P., Kulintang, M. B. M., Salas, C. J. C., Pechera, J. T., Mantilla, A. A. T., Mozar, E. K. G., ... Moro, J. B. (2024). Quality of prenatal care among mothers in selected barangays in Davao City, Philippines. *Journal of Interdisciplinary Perspectives*, 2(11), 53–65.

- Meadows, T., Coats, E. R., Narum, S., Top, E. M., Ridenhour, B. J., & Stalder, T. (2024). Epidemiological model can forecast COVID-19 outbreaks from wastewater-based surveillance in rural communities. *Water Research*, 268, 122671.
- Official Gazette. (2012, August 15). *Republic Act No. 10173: Data Privacy Act of 2012*. Retrieved from <https://www.officialgazette.gov.ph/2012/08/15/republic-act-no-10173/>
- PMNCH. (2023). *Maternal, newborn and child health (MNCH) strategy 2021–2025*. Geneva, Switzerland: Partnership for Maternal, Newborn & Child Health.
- Raghavan, S., Josey, K., Bahn, G., Reda, D., Basu, S., Berkowitz, S. A., ... Ghosh, D. (2021). Generalizability of heterogeneous treatment effects based on causal forests applied to two randomized clinical trials of intensive glycemic control. *Annals of Epidemiology*, 65, 101–108.
- Rajuroy, A., & Emmanuel. (2025). *Machine learning-based predictive models for mapping maternal and child health disparities using geospatial data*. ResearchGate.
- Sani, J., & Ahmed, M. (2025). Machine learning approach in predicting early antenatal care initiation at first trimester among reproductive women in Somalia: An analysis with SHAP explanations. *Intelligence-Based Medicine*, 11, 100252.
- Sun, K., Hu, Y., Lakhanpal, G., & Zhou, R. Z. (2023). Spatial cross-validation for GeoAI. In S. Gao, Y. Hu, & W. Li (Eds.), *Handbook of geospatial artificial intelligence* (pp. 201–214). Boca Raton, FL: CRC Press.
- Susukida, R., Amin-Esmaili, M., Badillo-Goicoechea, E., Nguyen, T. Q., Stuart, E. A., Rosenblum, M., ... Mojtatabi, R. (2024). Application of causal forest model to examine treatment effect heterogeneity in substance use disorder psychosocial treatments. *International Journal of Methods in Psychiatric Research*, 34(1), e70011.
- Togunwa, T. O., Babatunde, A. O., & Abdullah, K. R. (2023). Deep hybrid model for maternal health risk classification in pregnancy: Synergy of ANN and random forest. *Frontiers in Artificial Intelligence*, 6, 1213436.
- UNICEF. (2025). *Maternal and newborn health*. Retrieved from <https://www.unicef.org/health/maternal-and-newborn-health>
- World Health Organization. (2019, September 23). *Maternal health*. Retrieved from <https://www.who.int/health-topics/maternal-health>
- Wu, Z., Zhang, Y., & Zhang, M. (2023). Unveiling the causal effects of China's minimum living standard guarantee on household transportation expenditures: A causal forest analysis. *Transport Policy*, 159, 1–13.
- Yaya, S., Anjorin, S. S., & Adedini, S. A. (2021). Disparities in pregnancy-related deaths: Spatial and Bayesian network analyses of maternal mortality ratio in 54 African countries. *BMJ Global Health*, 6(2), e004233.
- Ziarelli, G., Pagani, S., Parolini, N., Regazzoni, F., & Verani, M. (2024). *A model learning framework for inferring the dynamics of transmission rate depending on exogenous variables for epidemic forecasts*. SSRN.

### Author(s) Information

#### Patrick Cerna

Mapua Malayan Colleges Mindanao, Gen. Douglas  
MacArthur Hwy, Matina, Davao City 8000  
Davao del Sur, Philippines  
ORCID iD: <https://orcid.org/0000-0002-2554-2098>

#### Raphael Mico Barrios

Mapua Malayan Colleges Mindanao, Gen. Douglas  
MacArthur Hwy, Matina, Davao City 8000  
Davao del Sur, Philippines  
ORCID iD: <https://orcid.org/0009-0007-3102-3837>  
\*Contact e-mail: [rmbarrrios@mcm.edu.ph](mailto:rmbarrrios@mcm.edu.ph)

#### JC-Rey Cata-al

Mapua Malayan Colleges Mindanao, Gen. Douglas  
MacArthur Hwy, Matina, Davao City 8000  
Davao del Sur, Philippines  
ORCID iD: <https://orcid.org/0009-0000-8024-781X>

#### Human Walter Olo

Mapua Malayan Colleges Mindanao, Gen. Douglas  
MacArthur Hwy, Matina, Davao City 8000  
Davao del Sur, Philippines  
ORCID iD: <https://orcid.org/0009-0005-9164-5051>

\*Corresponding author(s) contact email

### To cite this article:

Cerna, P., Barrios, R.M., Cata-al, J.C.R., & Olo, H.M. (2026). Geospatial causal inference for Barangay-level maternal care assessment: A causal forest framework on antenatal intervention outcomes in Davao city. *The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM)*, 41, 149-165.