Constructing a Predictive Crime Risk Assessment Mobile Application for Cities in Davao del Norte

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of the Requirements for the Degree
Master of Science in Information Technology

By
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Recommendation for Oral Defense

In partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN INFORMATION TECHNOLOGY**, *this* GRADUATE INDEPENDENT STUDY *entitled*

CONSTRUCTING A PREDICTIVE CRIME RISK ASSESSMENT MOBILE APPLICATION FOR CITIES IN DAVAO DEL NORTE

has been prepared and submitted by Angelica Morales Almuenda *and is recommended for* ORAL DEFENSE.

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The Graduate Faculty of the Computer Studies Cluster of the Ateneo de Davao University accepts the Graduate Independent Study entitled

CONSTRUCTING A PREDICTIVE CRIME RISK ASSESSMENT MOBILE APPLICATION FOR CITIES IN DAVAO DEL NORTE

which has been prepared and submitted by Angelica Morales Almuenda *in partial fulfillment of the requirements for the degree Master of Science in Information Technology.*

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Abstract

This study intended to answer the question "*What are the probable dangers of being in a vicinity of a specific place?*" One solution is to develop a crime predictive model to automatically measure the risk of an area based on several crime predictors using machine learning algorithm. As identified from the findings of other studies, crime rate are influenced by five different factors such as time and day, weather, social indicators, economic indicators, and types of places. These crime factors were elected to become independent variables for this study's predictive crime risk assessment model. The prediction model was trained using Random Forest Classifier algorithm as provided by Scikit Learn package in Python. The training and testing data samples were taken from three cities in Davao del Norte namely Tagum City, Panabo City, and Samal City. These data were indexed crime data from July 2017 to August 2018, with a total number of 1094 crime instances. There were 114 different independent variables to predict one dependent variable. The dependent variable had seven crime values: *carnapping, drug-related incident, murder/homicide, physical injuries, rape, robbery,* and *theft*. In the model evaluation, it was found out that each city had its own unique behavior when it comes to how predictors influence the probabilities. Therefore, one single model was not sufficient to generalize all three cities. To build separate predictive crime risk assessment model for each city was the most appropriate solution to reduce biases. All models, despite its undesirable performance scores, were able to calculate and display crime risks probabilities based on the predictor variables.

Additional Key Words and Phrases:

Data mining, Random Forest Classifier, Predictive modelling, Android application, Python

Chapter 1. Introduction

1.1 Background of the Study

Crime is a major concern of every citizen in any modern society. Anyone may become a victim of any crime. It is only needed to meet certain conditions for the perfect crime to take place. These conditions may be a combination of different risk factors such as the psychological state of a would-be offender (Hanson, 2009), socio-economic status (Bushway & Reuter, 2002), or even something as mundane as the weather (Cohn, 1990) and time of day (Felson & Poulsen, 2003). Among the risk factors, the most conspicuous is the location of crime. Citizens are always concern on their relative distance to the scene of the crime, how near or how far. Probably to approximate how severely they will be affected by the event. In a study by Schweitzer, et. al. (1999), it was found out that the presence of a nearby grocery or convenience store has a positive correlation both to the actual crime event and fear of crime felt by residents within the community. A similar study by Perkins et. al. (1993) also concluded that presence of non-residential property is related to serious crimes. This goes to say that a specific place has an influence, not just to the event of crime, but also to the fear of people regarding the probability of crime that may happen within the location.

The importance of the location of crime is emphasized in the development of various spatial statistics programs used by police departments for crime mapping (Levine, 2006) and crime hotspot analysis applications (Wang, et al., 2013). According to Block and Block (1995), though difficult to evaluate, somehow the connection between an offender and a victim lies on the conditions of the specific place where the interaction happens. Moreover, the characteristics of certain places affect the conditions of a certain area. For example, the fact that liquor-related violence is more concentrated in areas where bars and taverns are located (Block & Block, 1995).

Crime forecasting and crime mapping depends heavily on location data of crimes which agrees to Cohn's study (1990) stating that some aspects of the physical environment have considerable impact on people's behavior. From the police perspective, the importance of crime forecasting involves strategy and decision-making for police-related matters, some of which includes the proper deployment of vehicles and personnel to specific areas (Gorr, Olligschlaeger, & Thompson, 2000), dissemination of crime prevention programs for citizens occupying critical areas, and to track movements of serial offenders (Levine, 2006).

1.1.1 Crime in Davao Region

In the interest of places and its crime-related factors, it is curious to find out its significance within the locality of Davao Region. As shown in Figure 1.1 with data taken from the 2017 Philippine Statistical Yearbook, Davao Region has more incidents of crime per 100,000 population than the national overall count. This is consistent for six consecutive years from 2009 up to 2014. The data shows that crime rate in Davao Region is more than the average and more people are affected by crime in the location. Figure 1.2 shows that the types of crime with the highest number of incidents in Davao Region are Theft (16,694), Physical Injuries (15,143), and Robbery (6,008) from the year 2013 up to 2014. The quantity of crime incidents ensures enough crime data for research.

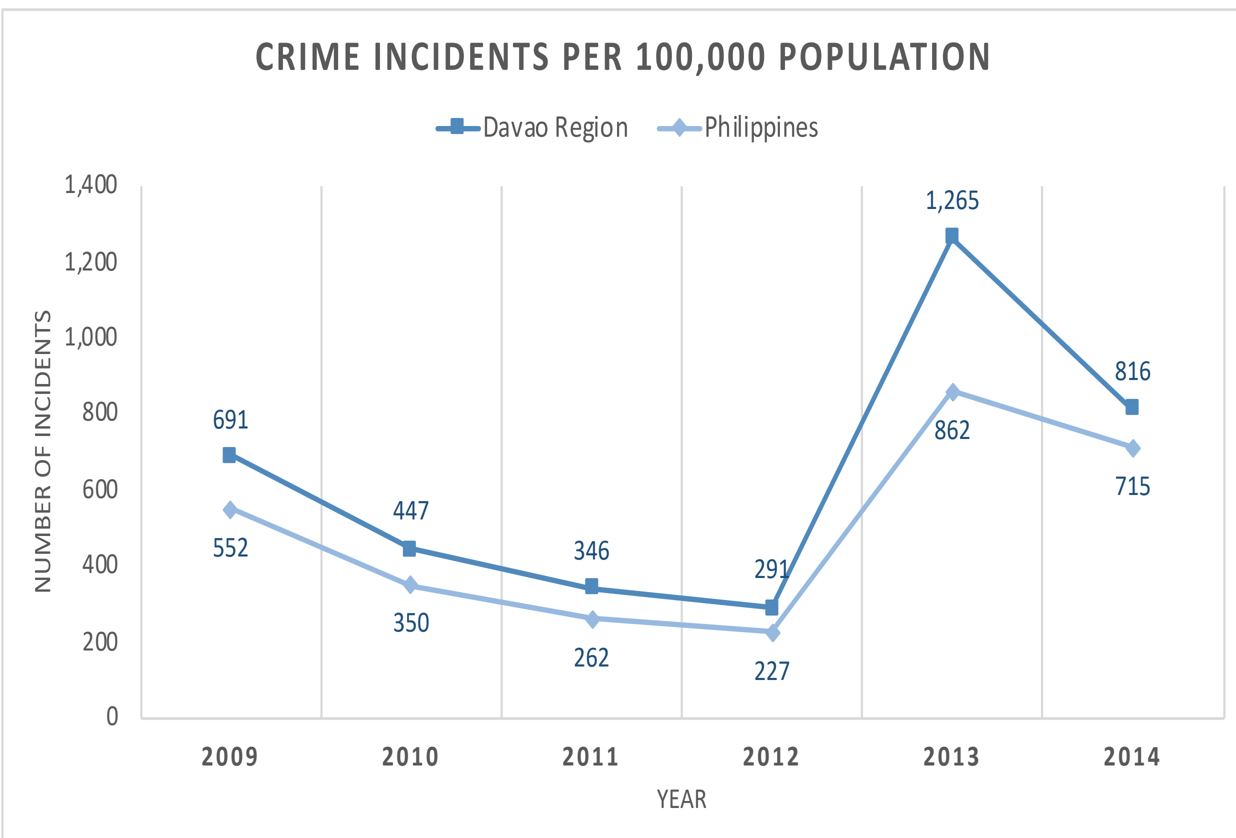


Figure 1.1 Crime Incidents in Davao Region Compared to Philippines

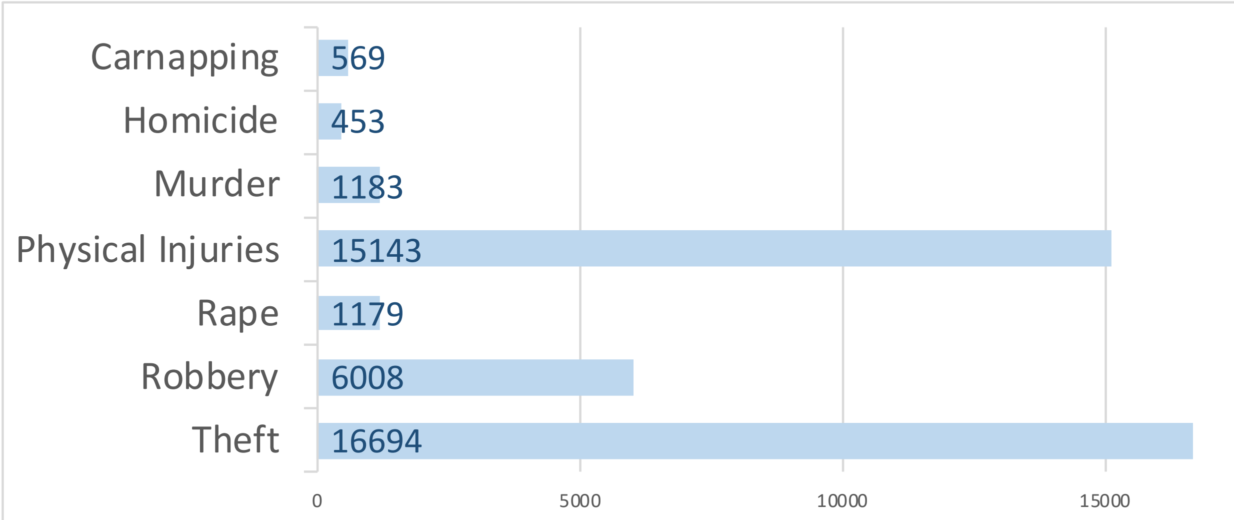


Figure 1.2 Davao Region Crime Count by Type 2013-2014

1.1.2 Crime Reporting and Information Access

In 2016, the Philippine National Police (PNP) launched two mobile applications named *Crime Reporting Mobile App* and the *BantayKrimen App*. The *Crime Reporting Mobile App* was developed as a supplement to the National Emergency Hotline 911. The *BantayKrimen App* serves as a community-based tool to promote crime awareness. In this application, users will be able to view history of crime incidents plotted on the map. Though the features of the application were helpful enough to the public, it does not have a predictive mechanism. This study aims to extend the ability of the existing crime awareness application into a predictive crime risk assessment application. The difference between the two lies on the former is being a historical data and the latter being a forecasting application.

1.2 Statement of the Problem

"How safe is a place from crime?" That is the question this study meant to give answer to. This study will use past records of crime to create a forecasting model of crime occurrence. Specifically, the following problems must be solved to realize the implementation of a predictive crime risk assessment application:

- What are the factors that affect crime?
- How to construct a predictive model for crime using these factors?
- How reliable is the crime predictive model?
- How to implement the crime predictive model in a mobile application so it will produce risk probabilities for each crime type?

1.3 Objectives of the Study

The successfully implement a predictive crime risk assessment application, this study intents to:

- ♦ Identify factors that affect crime as mentioned by other studies.
- ♦ Construct a predictive model for crime using the factors identified.
- ♦ Evaluate the performance of the crime predictive model.
- ♦ Implement the crime predictive model in a mobile application that will be able to calculate risk probabilities of each crime type based on predictor values.

1.4 Significance of the Study

1.4.1 General Public

Though there are various crime forecasting programs, most of its implementation was designed for use by law enforcement agencies and not available to the general public. From the perspective of a simple citizen, this type of program may be used to distance oneself from becoming a crime victim. Moreover, the artifact of this study may be used as a safety tool to ease the psychological distress brought by fear of crime in a certain place (Schweitzer, Kim, & Mackin, 1999). In the Philippines, a crime mapping application officially hosted by the PNP and available for public consumption has the capability to inform the user of the past crimes that has happened within a specific location. This application is called *BantayKrimen App* and is undeniably informative when it comes to crime records. However, it is limited to the past and cannot inform the user of the probable crimes that might happen within a location in the future. The crime assessment programs currently available to the public are not forecasting applications. This study aims to bridge the gap between the law enforcement and the general masses with regards to accessibility to crime prediction program. This goal can be achieved by developing a mobile application with predictive capabilities for crime risk assessment.

1.4.2 Other Students and Researchers

The construction of a predictive model based on several crime factors may unveil findings which will be valuable to future studies. The methods and results may become useful to other students and researchers who have similar subject interest.

1.5 Scope and Limitations of the Study

1.5.1 Crime Classes

The model is a classification model that can predict probabilities of the following crimes: *Murder/Homicide, Physical Injuries, Drug Related Incident, Theft, Carnapping, Rape,* and *Robbery*. The crime prediction model is limited to the indicated crimes. Other crime types are not included in the model.

1.5.2 Local Implementation

The model is trained and tested using crime data of Tagum City, Panabo City, and Samal City. Thus, the scope and implementation of this research is limited to the locality of mentioned cities which are within the Administrative province of Davao del Norte.

1.5.3 Technical Implementation

The mobile application is developed as a prototype for the Android mobile operating system. The mobile application will be tested on an Android phone with an Oreo firmware version. The mobile application is only a prototype and may not work properly in earlier versions of the Android operating system.

Chapter 2. Review of Related Works and Literature

The crime prediction in terms of location is not a new knowledge. However, the first known application of technology to crime prediction has only been introduced in 2008. Nevertheless, the concept of location and crime prediction was explored by Sherman et. al. in as early as 1989 by mapping police calls and the addresses where the calls were made from (Sherman, Gartin, & Buerger, 1989). Though the study conducted by Sherman et. al. (1989) was purely for knowledge discovery and not for forecasting, they have successfully figured out top crime hotspots for robbery, auto theft, and rape in the community. The absence of capable technology, such as data mining, did not stopped researchers in the 1980s from attempting to uncover truths about crime and location. But with the advancement of technology and data science in the early 2000s, crime prediction applications were made possible to serve a wider audience than the law enforcement. Several modern crime prediction applications were developed over the years and it is one of the aims of this study to review the objective, methodologies, and results of existing technologies relevant to this topic. There are many ways in which crime predictive modelling were applied. However, this study will focus on studies regarding crime prediction in the context of location and space. There are also many theories surrounding crime forecasting, however, these will only be referenced as appropriate and will not be reviewed in details since the focus of this study is the implementation of a crime prediction system.

The original objective of developing a crime forecasting technology was to assist police in resource allocation. The limited manpower and police transport vehicles means that only a few places can be under surveillance at any given time. Crime can happen anywhere and thus the deployment of police resources must be in the right place at the right time in order to prevent crime or catch a criminal. In the year 2008, instead of relying fully to chance and luck, police chief at that time, William J. Bratton of the Los Angeles Police Department pioneered the development of a crime model which can mathematically calculate where and when crime is likely to happen. He called this crime predictive technology *Predictive Policing (PredPol)* which he developed to increase police response and performance by deploying officers according to the output of the program (Rienks, 2015). This program is still in use to the present by law enforcement agencies in the US. This was even noted to have influenced the overall 2% decline of crime rate in Merced from 2015 to 2016 (Miller, 2017) and attracted media interest when the program enabled the arrest of would-be offenders before a crime took place in a high-risk area (Perry, Walt L, 2013). Though the inner-workings of the *PredPol* program is not disclosed to public due to its copyright, it was reported that its algorithm is similar to a mathematical model used to predict earthquake aftershocks (Shaw, 2017).

2.1 Common Trends in Predictive Modeling

2.1.1 Classification Models

The purpose of applying classification models to crime forecasting varies among several studies. However, the typical goals of applying classification is to predict crime event either according to the type of crime that may happen given a particular place at a given time (Almanie, Mirza, & Lor, 2015; Cherian & Dawson, 2015) or according to the intensity of a hot spot (i.e. low, medium, high) within a specified area (Yu, Ward, Morabito, & Ding, 2011; Ahishakiye, Taremwa, Opiyo, & Niyonzima, 2017). It is also observable among past studies to compare classification techniques with each other to know what gives the most accurate and precise prediction. Naïve Bayesian Classifier, Decision Tree Classifier, Random Forest, Nearest Neighbor, and Support Vector Machine are among the commonly used and compared techniques. Apriori Algorithm and Neural Networks were also mentioned albeit not as much. The performance of each technique vary among studies, one technique that has performed well in one study may not be a good technique to use for another study.

2.1.2 Crime Mapping

Similar to Spatial Cluster Analysis which uses GIS as a visualization tool, crime mapping does not only show where in the map a crime has happened, but can also show the crime density and distribution on an area. This technique is what many studies use for hot spot identification (Rosser, Davies, Bowers, Johnson, & Cheng, 2017; Achu & Rose, 2016; Cohen & Gorr, 2005; Wang, et al., 2013; Ferreira, João, & Martins, 2012). This technique is commonly implemented three ways: cluster (Figure 2.1), grid (Figure 2.2), or street network (Figure 2.3). Clustering is the grouping of several crime points on the map which are close to each other. Basically, clusters points which are concentrated in a particular area. The use of grid system is to divide an area into equally-sized grids then it will show which grids have more or less crimes. The use of street networks is specifically applied by Rosser et. al. in their study in which they argue that crime usually happens along or on the streets (2017). This also implies that the spread of hot spot may not be circular from the crime center point, as with clustering and grid, but rather follow the street networks. Crime mapping technique is particularly useful for area monitoring and surveillance.

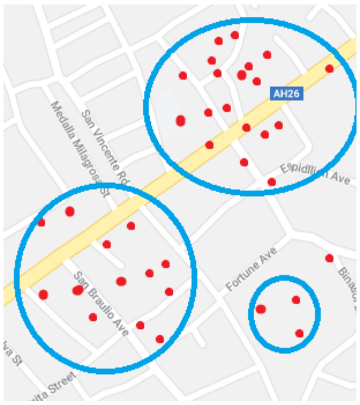


Figure 2.1 Cluster

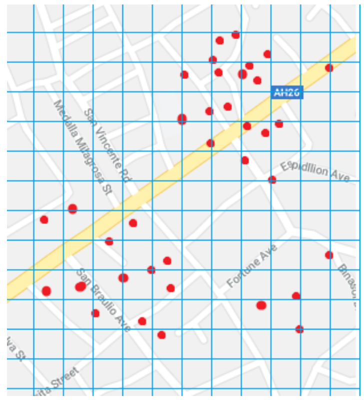


Figure 2.2 Grid

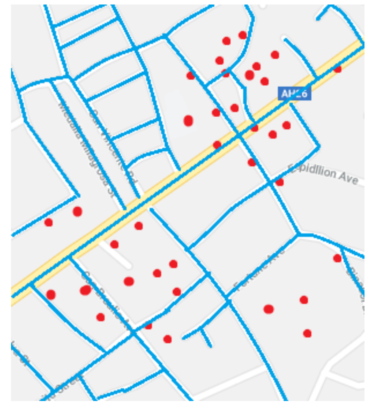


Figure 2.3 Street Network

2.1.3 Time Series Analysis

Time Series Analysis is concern about crime trends over time. It usually wants to answer which time and day, month, season, or year a crime is mostly likely to happen. According to studies (Gorr, Olligschlaeger, & Thompson, 2003; Cherian & Dawson, 2015; Cohen & Gorr, 2005; Rubio, Ballera, & Gonzales, 2018), time trend is dependent on the type of crime. An example is that property crime levels usually increase at the end of year holidays and aggression crimes are at peak during the summer months (Gorr, Olligschlaeger, & Thompson, 2003). If combined with crime mapping, time series analysis can be used to measure how crime within specific area increase or decrease overtime as demonstrated in the study by Cohen (2005) and Gorr (2003). The commonly used data mining technique for time series analysis is exponential smoothing.

2.2 Existing Applications

2.2.1 Risk Terrain Modeling

Crime mapping is a very useful tool; however, its limitations lies on the fact that it only limits the crime information to a certain point on the map and does not go beyond what lies within. It would help to remember that a point on the map is a physical environment in which several attributes might be present. A point might be inside a mall, or in the middle of a mountain, along a busy street, or on a pavement. All this information is not considered in crime mapping models until the introduction of a crime prediction technique called Risk Terrain Analysis (RTM). RTM is an approach to risk assessment developed by Caplan and Kennedy (2011) which expanded the use of GIS in the context of crime. This particular model is not dependent on location point of the map, but rather to the risk factors present within the location point which are related to crime. Risk factors are maybe in the form of establishments such as banks, bars, apartments, coffee shops, clinic, library, many other physical structures in the vicinity. This particular software is available for desktop and can be used as a software-as-a-service with subscription pricing. The main feature of the program is the risk terrain maps which will produce hot spots of crime type of interest within a particular area at a given time. It also uses equally sized grid system to represent surfaces on the map. This software has been used for the purpose of police resource allocation (Kennedy, Caplan, & Piza, 2011) and vulnerability exposure assessment of assault crime (Kennedy L. W., Caplan, Piza, & Buccine-Schraeder, 2016).

2.2.2 Environmental Design Applications

Another way to apply crime mapping into a system is to survey the actual conditions of the physical environment where a crime happened. Two studies (Tabangin, Flores, & Emperador, 2010; US Patent No. 8,515,673, 2013) has presented this kind of crime prediction technique by taking into consideration both the crime event and the environmental design where the crime took place. This has similar methodology with RTM but this application took it to the next level by adding information with regards to building design, land use, territorial signage, and physical deterioration or disorder of the place (Tabangin, Flores, & Emperador, 2010). Using Decision Tree Algorithm, Tabangin et. al. (2010) applied this crime prediction concept in Baguio City where they found out theft and robbery occur more on open-air commercial areas and areas with poor visibility from the public. Physical injuries are more likely to occur in the presence of liquor establishments and transport terminals. Majority of hot spots are situated within dark alleys and old run-down buildings. The study by Tabangin et. al. (2010) was not an automated application and they manually surveyed and took photos of chosen crime location points to know the condition of a place. Though this is the case, this model has a lot of potential to become a crime predictive system. Whereas, the crime risk assessment system developed by Trinko and Trinko (2013) depends on Google Street View images to assess the condition of an area.

Considering the environmental design in terms of predicting where crime is likely to happen can build a dynamic system since it is not restricted by a crime location point. This technique, however, requires a lot of work when it comes to information collection about the status and conditions of an area. Not to mention, since places deteriorate with time or maybe renovated by new owners, the reliability of this system maybe limited unless those place condition data are always up to date.

2.2.3 Descriptive Applications

The goal of a descriptive application is not to predict but rather to summarize past crime data into a readily understandable format for reference. Three studies (Sandig, Somoba, Concepcion, & Gerardo, 2013; Ramos, et al., 2017; Kadar & Cvijikj, 2014) are identified to have developed descriptive crime systems and observed that they all have a common goal. All three researches aimed to display map point locations of past crimes and then show the crime density/frequency within an area for the purpose of information dissemination. All of the mentioned studies are also available both as a mobile and web application. Since the solution is very straightforward and most programming languages already offer basic data mining algorithms, this type of crime system is fairly uncomplicated to implement given a reliable data is at hand. However, this kind of system will not be able to produce statistical results on map points where crime did not happen.

2.2.4 Prescriptive Applications

Unlike descriptive and predictive applications, the goal of a prescriptive system is not only to inform but also to advice the user on what action is best to take according to a given situation. Two crime-related applications were identified to have this kind of concept. One application is a warning system which recommends where to allocate police officers for surveillance according to the current state of hotspot intensity within the cities of Caloocan, Malabon, Navotas, and Valenzuela (CAMANAVA) (Rubio, Ballera, & Gonzales, 2018). The system made use of the crime mapping cluster to visualize hot spots for different types of crime according to month, day of the week, and hour. Then if an area has high crime intensity, it will then pop-up a recommendation to deploy police resources on that specific location. The other application involves a mobile application which can find safe roads to navigate (Mata, et al., 2016). The main objective is to try and avoid traveling through a hot spot area. It involves semantic analysis and spatiotemporal analysis of tweets from twitter and from official crime records to generate safe routes. The safe routing algorithm made use of crime mapping street network nodes as baseline to points where past crimes happened. The greater the distance of the street from crime points, the safer it is. This safe-routing application is the only application mentioned in this review that a non-police user may use.

Chapter 3. Research Frameworks and Design

3.1 Theoretical and Conceptual Framework

The theoretical assumption of this study is based on the theory of crime and places which stated that *conditions of the physical environment attracts specific types of crime*. This theory is illustrated in Figure 3.1.

Figure 3.1 Theoretical Framework

The conditions of a place varies among other studies, however this study specifically determines the conditions of an environment as *Time/Day, Weather, Socioeconomic Profile, and Type of Place*. These are assumed to be relevant crime predictors since the society, as a whole, experiences all these factors. Figure 3.2 show that the model uses these conditions to produce probability predictions of each crime type.

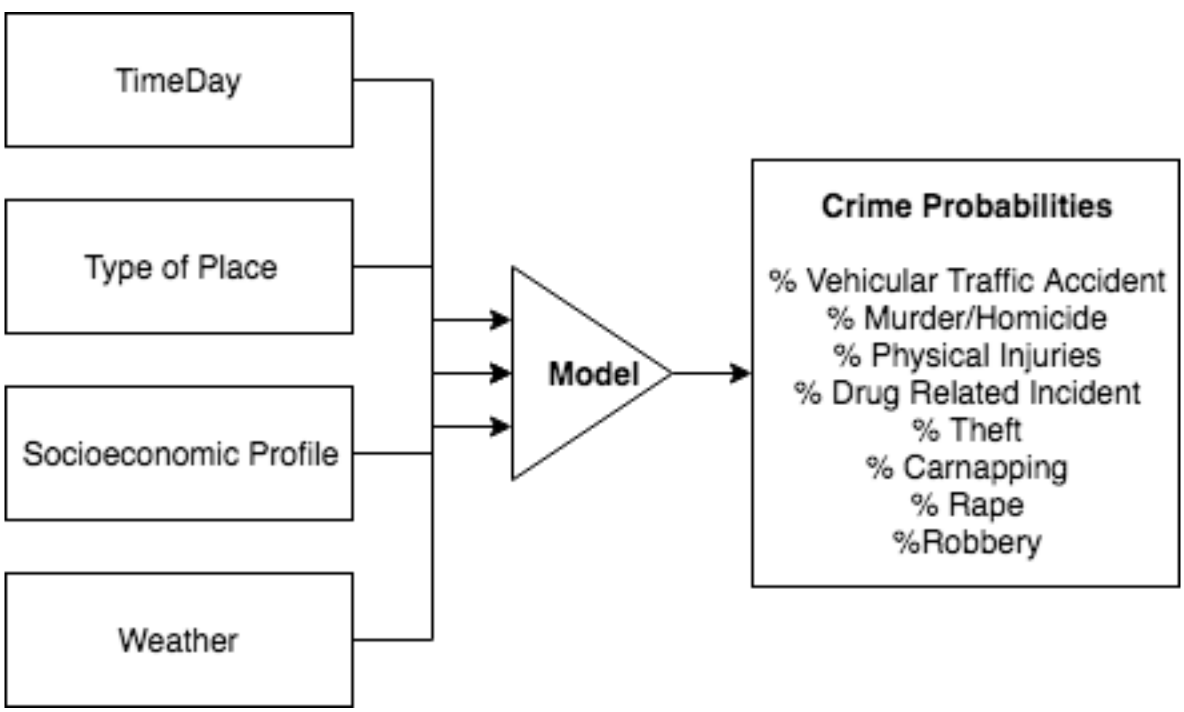


Figure 3.2 Conceptual Framework

Figure 3.3 shows that a mobile application for Android operating system is used to access the trained model on the web server. The mobile interface is necessary to get new values of each input feature from the user for risk assessment calculations. The web server is written in Python which uses the web framework Flask to handle HTTP requests. The predictive model is constructed using Random Forest Classifier algorithm from a Python-based machine learning package called Scikit Learn.

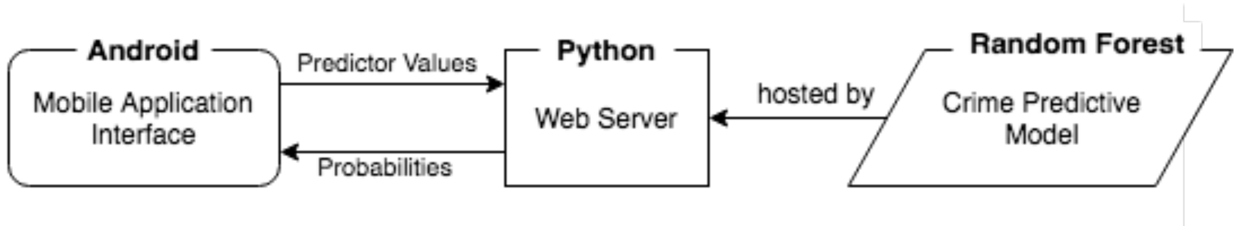


Figure 3.3 Model Implementation on Mobile Application

3.2 Methodology

Figure 3.4 summarizes the research process from start to finish. This study undergoes six steps in order to achieve the objectives written in the Introduction chapter. The major steps includes *data gathering, data integration, data cleaning and transformation, model training, model evaluation, and model implementation*.

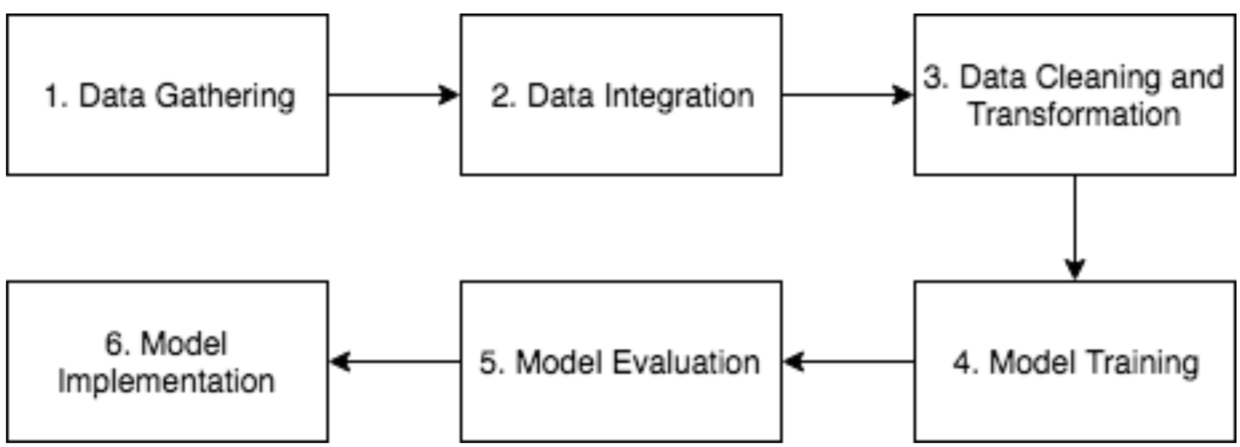


Figure 3.4 Methodology

Chapter 4. Results and Discussion

4.1 Data Gathering

4.1.1 Crime Indicators

The following types of predictors were chosen specifically on their relevant effects to various crimes as studied by other researchers. Incorporating these factors into building a crime predictive model may prove significant to increase its reliability.

♦ ***Time/Day*** variables were specifically selected due to routine activity theory (Cohen & Felson, 2016). Cohen and Felson (1979), through this theory, explained that crime event depends on the presence or absence of three controllers called *intimate handlers, guardians, and place managers*. The presence of one or more of these controllers tends to prevent crime from happening. Since over the course of day, controllers tend to shuffle from place to place, this study recognized the importance of time and day as independent variables. There are times and days when there are complete absence of all controllers in a specific place and thus making it easier for the offender to commit crime against a target.

♦ ***Type of Place***. Though the majority of crime prevention theory focuses on the greater neighborhood, Eck and Weisburd (2015) said that there is a shift of that focus to smaller space of places. They compiled several studies which focus on the influence of places to crime. These studies has findings on different facilities such as the following:

- ◊ Bars, housing projects, and high schools influence the increase of crime counts within the blocks they are located.
- ◊ Presence of hotels is associated with higher crime rates per thousand people. It particularly influences auto and assault crimes.
- ◊ There is a positive correlation between the presence of residential homes and crime.
- ◊ Burglaries are also found to be correlated to presence of restaurants, supermarkets, department stores, and bars.

Eck and Weisburd (2015) came to the conclusion that places that are accessible and attract large number of people have higher victimization rate.

♦ ***Socioeconomic Indicators***. Social variables are the number of population belonging to a specific demographic. The scope of social variable values is the population residing within each barangay (neighborhood). Economic variables refer to factors which influences the Philippine economy in general. According to several studies, the following socio-economic indicators influence crime rates: *unemployment, labor force, income, population, poverty, transience, level of educational achievement, and deposit rates* (Weatherburn, 1992; Iqbal, Murad, Mustapha, Panahy, & Khanahmadliravi, 2013; Kitchen, 2006; Daday, Broidy, Crandall, & Sklar, 2005; United Nations Office on Drugs and Crime, 2011; Buonanno, 2003).

♦ ***Weather***. Ranson (2014) studied the effects of climate change to criminal activity in the United States and found out that there is a positive correlation between the two. Moreover, he said that climate change affects the economy. Ranson found out in his study that weather affects incidence of crime. For instance, high temperature leads to higher crime rates on all crime categories except manslaughter; while low temperature leads to property crime. Cohn (1990) also compiled several findings on the relationship between weather and crime. He found out that heat and some crimes such as collective violence, assault, rape, domestic violence, and burglary have positive association. Other factors that have positive correlation with each other include cold temperature and robbery, sunlight and assault, rain and robbery, wind and homicide.

4.1.2 Crime Data

Crime data of Tagum City, Panabo City, and Samal City were from taken from the Philippine National Police (PNP) website. It is available as public information that maybe copied or distributed within the boundaries of the law (Philippine National Police, 2019). The crime data did not include blotter reports due to public access restrictions and privacy protection of individuals involved. However, the publicly-available crime data was sufficient enough since it has all the relevant information needed by this study to build a crime predictive model. The data contained crime-related information such as *crime, barangay, city, date, time,* and *latitude/longitude of the place of crime*. The crimes in the dataset happened from July of 2017 up to August of 2018.

4.1.3 Weather Data

Weather data was based from daily historical weather data of Tagum City, Panabo City, and Samal City provided by World Weather

Online website. This data contained *date, time, weather type, temperature, wind velocity, cloud cover percentage, humidity percentage, precipitation, pressure, sunrise time,* and *sunset time*.

4.1.4 Places Data

Places referred to the kinds of facilities, infrastructures, or natural environment surrounding a vicinity of crime. This study included known places within 200 meters of a map point where crime happened. These data were downloaded from Open Street Maps using a Python API. This study has limited the kinds of places to 40 types such as *Bank, Bar, Beach, Bridge, Cemetery, Church, Clinic, Commercial Building, Community Center, Convenience Store, Fire Station, Gas Station, Government Office, Greenfield, Highway, Highway Pedestrian, Highway Primary, Highway Residential, Highway Secondary, Highway Tertiary, Hospital, Hotel, Industrial Building, Mall, Marketplace, Park, Parking Area, Pawnshop, Pharmacy, Police Station, Post Office, Private Office, Recreational Area, Residential Building, Restaurant, Road, School, Sports Center, Tourist Attraction,* and *Transport Terminal*.

4.1.5 Economic Data

Economic data included daily historical data of PHPUSD exchange rate, daily historical data of Philippine Stock Exchange index, and monthly historical data of Consumer Price Index (*all items, alcoholic beverages and tobacco, transport, housing, water, electricity, gas, and other fuels, restaurant and miscellaneous goods and services*), inflation rate, savings deposit interest rate, and bank lending rates. Data were taken from Bangko Sentral ng Pilipinas and Philippine Statistics Authority' Monthly Statistical Indicators report for November 2018 (Bersales, 2018).

4.1.6 Social Data

The social data includes number of population belonging to a certain demographic. The total population data per barangay were already available in raw format from PSA. All other social variable values were derived from the total population using percentages for Davao Region or by city depending on the available information. Demographic variables include education, household, housing, labor, marital status, population age structure, and poverty. All data are taken from the Philippine Statistics Authority reports.

$$Household\ Population = \frac{Total\ Population\ (Barangay)}{Average\ Household\ Size}$$

Equation 4.1 Household Population

♦ **Household Data**. Household population was calculated using Equation 4.1 where *Average Household Size* values were Samal City = 3.97, Panabo City = 4.33, and Tagum City = 4.29.

Highest Education Completed	Panabo City	Samal City	Tagum City
No grade completed	0.50%	1.14%	0.54%
Elementary	20.93%	34.28%	17.95%
High school	46.95%	44.16%	41.13%
Postsecondary	2.93%	1.86%	4.49%
College undergraduate	13.29%	9.51%	15.43%
Baccalaureate graduate	15.21%	8.88%	20.08%
Post baccalaureate	0.14%	1.86%	4.49%

Table 4.1 Percentage of Highest Education Level by City

$$Highest\ Educational\ Level = Population\ (20\ Years\ And\ Over) \times Percentage$$

Equation 4.2 Population by Highest Educational Level

$$Out\ of\ School\ Youth = Population\ (5\ to\ 24\ years\ old) \times Percentage$$

Equation 4.3 Population of Out of School Youth

♦ **Education Data**. Highest education level achieved by the population was computed using Equation 4.2. Educational level achieved includes *no grade completed, elementary, high school, postsecondary, college undergraduate, baccalaureate graduate,* and *post-baccalaureate*. Table 4.1 shows the percentages of the population with corresponding highest educational level by city. The out of school youth predictor was calculated using Equation 4.3 with percentage of Out of school youth at 9.11% in the country as indicated by *2017 Annual Poverty Indicators Survey* PSA report.

Dwelling Status	Percentage
Own house rent lot	1.42%
Own house rent-free lot with consent of owner	15.80%
Own house rent-free lot without consent of owner	1.38%
Own or owner-like possession of house and lot	68.05%
Rent house/room including lot	5.45%
Rent-free house and lot with consent of owner	7.78%
Rent-free house and lot without consent of owner	0.15%

Table 4.2 Dwelling Status Percentage (Davao Region)

$$Dwelling\ Status = Population\ (Barangay) \times Percentage$$

Equation 4.4 Population by Dwelling Status

♦ **Dwelling Status Data**. Dwelling status refers to the different kinds of living conditions of the population. This variable was calculated using Equation 4.4. Percentages of the population's dwelling status for Davao Region are shown in Table 4.2.

$$Labor\ Force\ Participation = Population\ (15\ years\ and\ above) \times 59.60\%$$

Equation 4.5 Population in the Labor Force

$$Not\ in\ Labor\ Force = Population\ (15\ years\ and\ above) \times 40.41\%$$

Equation 4.6 Population Not in the Labor Force

$$Unemployed = Labor\ Force\ Participation \times 5.36\%$$

Equation 4.7 Unemployed Population

$$Employed = Labor\ Force\ Participation \times 94.64\%$$

Equation 4.8 Employed Population

$$UnderEmployed = Employment\ Rate \times 15.4\%$$

Equation 4.9 Underemployed Population

♦ **Labor Force Data**. Population in the labor force was calculated using Equation 4.5; while Equation 4.6 was used for population not participating in the labor force. Employment rate was computed using Equation 4.8, unemployment rate was computed using Equation 4.7, and underemployment rate was calculated using Equation 4.9. The percentages were based on the PSA report in *Percent Distribution of Population 15 years old and over by Employment Status*.

$$Poor\ Families = Total\ Population\ (Barangay) \times 16.6\%$$

Equation 4.10 Number of Poor Families

$$Poor\ Individuals = Total\ Population\ (Barangay) \times 22.0\%$$

Equation 4.11 Number of Poor Individuals

$$Poor\ Employed\ Individuals = Employed\ Population \times 16.5\%$$

Equation 4.12 Number of Poor Employed Individuals

$$Poor\ Unemployed\ Individuals = Unemployed\ Population \times 18.1\%$$

Equation 4.13 Number of Poor Unemployed Individuals

- **Poverty Data**. Poverty incidence by demographic was calculated using Equation 4.10, Equation 4.11, Equation 4.12, and Equation 4.13. Percentages of poverty incidence were taken from the report for Davao Region in *2017 Regional Social and Economic Trends*.
- **Population Data**. Population count came from the 2015 Census of Population (2017) report by Philippine Statistics Authority. To lessen the number of independent variables, the age brackets of the population were sorted into four categories namely *children (ages 0 to 9 years old), teenage (ages 10 to 19 years old), adult (ages 20 to 59),* and *retiree (ages 60 and above)*. Moreover, the genders (*male or female*) of each age category were also included as predictors.

4.2 Data Integration

Data integration was done manually through Pandas Python library. Data was integrated by merging crime data with weather, places, economic, and social data. Crime data and weather data were merged using columns *city, time,* and *date*. Crime data and places data were merged using columns *latitude* and *longitude*. Crime data and economic data were merged using columns *date* for daily data and *month* and *year* for monthly data. Crime data and social data were merged using columns *city* and *barangay*. Code 4.1 shows the code for all data integration by using the *merge* function.

Code 4.1 Data Integration

```
import pandas as pd

crime_data = pd.read_csv('crime_ddn_city.csv', encoding='utf-8')
crime_data['weathertime'] = crime_data.apply(lambda row: convert_to_weather_time(row['time']),axis=1)
crime_data['time_epoch'] = crime_data.apply(lambda row: convert_to_time_bin(row['time']),axis=1)
crime_data['day'] = crime_data.apply(lambda row: convert_to_day(row['date']),axis=1)

# merge crime and weather
weather_data = pd.read_csv('weather_davaodelnorte_data.csv', encoding='utf-8')
crime_data = pd.merge(crime_data, weather_data,
                      how='left',
                      left_on=['city','date','weathertime'],
                      right_on=['city','date','weathertime'])

# merge places and crime
places_data = pd.read_csv('places_crime.csv', encoding='utf-8')
crime_data = pd.merge(crime_data, places_data,
                      how='left',
                      left_on=['lat','lng'],
                      right_on=['lat','lng'])

# merge currency, psei, and crime
phpusd_psei = pd.read_csv('php_to_usd_data.csv', encoding='utf-8')
crime_data = pd.merge(crime_data, phpusd_psei,
                      how='left',
                      left_on=['date'],
                      right_on=['date'])

# merge social and crime
socio_data = pd.read_csv('ddn_socio.csv', encoding='utf-8')
crime_data = pd.merge(crime_data, socio_data,
                      how='left',
                      left_on=['barangay','city'],
                      right_on=['barangay','city'])

# merge economic and crime
eco_data = pd.read_csv('monthly_eco.csv', encoding='utf-8')
crime_data = pd.merge(crime_data, eco_data,
                      how='left',
                      left_on=['year','month_num'],
                      right_on=['year','month_num'])
```

4.3 Data Cleaning and Transformation

After having a compilation of all predictor data, crime classes were converted into numerical labels, shown in Table 4.3, by *label encoding*. The table shows all the label values of one dependent variable (crime label). The time of crime was sorted into categories namely *After Midnight (00:00 - 03:59), Early Morning (04:00 - 07:59), Morning (08:00 - 11:59), Afternoon (12:00 - 15:59), After Work-Hours (16:00 - 19:59),* and *Evening (20:00 - 23:59).* Sunrise and sunset time were transformed into two columns namely *daylight* (if crime happened when the sun is out) and *nighttime* (if crime happened during the darkness of the night). Categorical columns (*time, day, weather, daylight or nighttime, rural or urban, and places*) were transformed into numerical data using *one-hot encoding*. Crime data duplicates were removed and unnecessary columns were dropped. The complete list of independent variables is shown in Table 4.4.

Crime	Numerical Label
Carnapping	0
Drug Related Incident	1
Murder/Homicide	2
Physical Injuries	3
Rape	4
Robbery	5
Theft	6

Table 4.3 Dependent Variable: Crime Values

Variable Type	Value Type	Features (count = 114)
Weather	Numerical	Temperature (degrees Celsius), Temperature - Feels Like (degrees Celsius), Wind Velocity (km/h), Cloud Coverage, Humidity, Precipitation (mm), Barometric Pressure (mb)
	Nominal 0 or 1	*Weather* [Clear, Cloudy, Rainy]
Places	Nominal 0 or 1	Bank, Bar, Beach, Bridge, Cemetery, Church, Clinic, Commercial Building, Community Center, Convenience Store, Fire Station, Gas Station, Government Office, Greenfield, Highway, Highway Pedestrian, Highway Primary, Highway Residential, Highway Secondary, Highway Tertiary, Hospital, Hotel, Industrial Building, Mall, Marketplace, Park, Parking Area, Pawnshop, Pharmacy, Police Station, Post Office, Private Office, Recreational Area, Residential Building, Restaurant, Road, School, Sports Center, Tourist Attraction, Transport Terminal
Economy	Numerical	PHPUSD-rate, PSE-index *Consumer Price Index* [All items, Alcoholic beverages and tobacco, Transport, Housing water electricity gas and other fuels, Restaurant and miscellaneous goods and services] Inflation rate, Savings Deposit interest rate, Bank Lending rates
Social	Numerical	*Education* [Baccalaureate graduate, College undergraduate, Elementary, High school, No grade completed, Out of school youth, Post baccalaureate, Postsecondary] Number of Households *Dwelling Status* [Own house rent lot, Own house rent-free lot with consent of owner, Own house rent-free lot without consent of owner, Own or owner-like possession of house and lot, Rent house/room including lot, Rent-free house and lot with consent of owner, Rent-free house and lot without consent of owner] *Labor* [Employed, In the Labor Force, Not in the Labor Force, Underemployed, Unemployed] *Poverty Incidence* [by employed, by household, by population, by unemployed] *Population* [Children, Teenage, Adult, Retiree, Female Children, Female Teenage, Female Adult, Female Retiree, Male Children, Male Teenage, Male Adult, Male Retiree]
	Nominal 0 or 1	*Place Type* [rural, urban]
Time/Day	Nominal 0 or 1	*Time Epoch* [After Midnight, After Work-Hours, Afternoon, Early Morning, Evening, Morning] *Day* [Friday, Monday, Saturday, Sunday, Thursday, Tuesday, Wednesday] *Day or Night* [daylight, nighttime]

Table 4.4 Independent Variables

4.4 Model Training

The predictive model was trained using crime data with distribution illustrated in Figure 4.1. The compiled data has 1,094 total crime instances. Crime data for Tagum City has a total of 803 crimes, Panabo City has 190 crimes, and Samal City has 101 crimes. The distribution of crime data by city is illustrated in Figure 4.2.

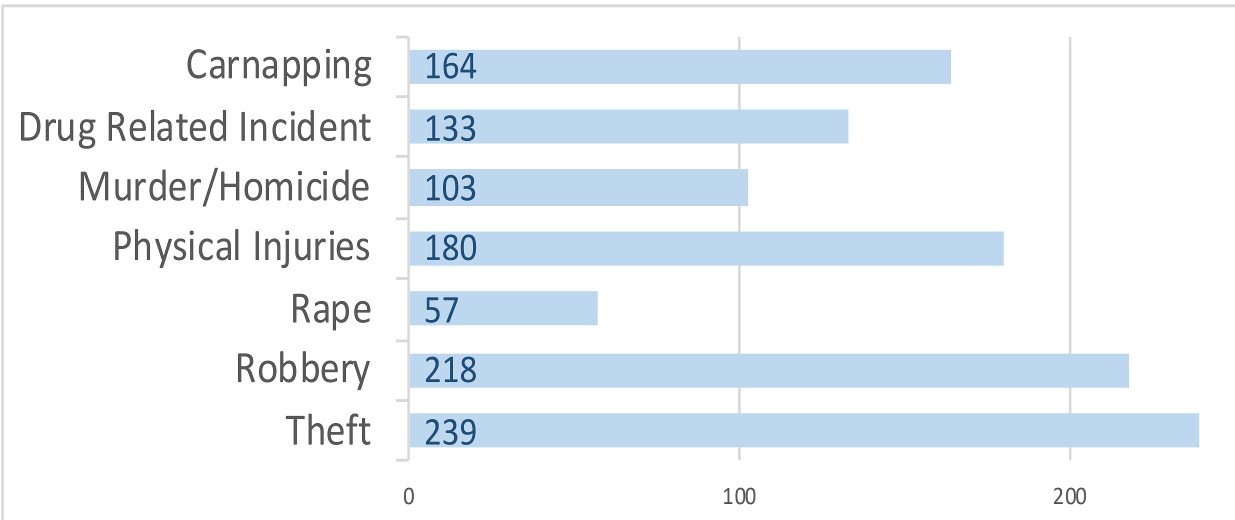


Figure 4.1 Crime Data Distribution

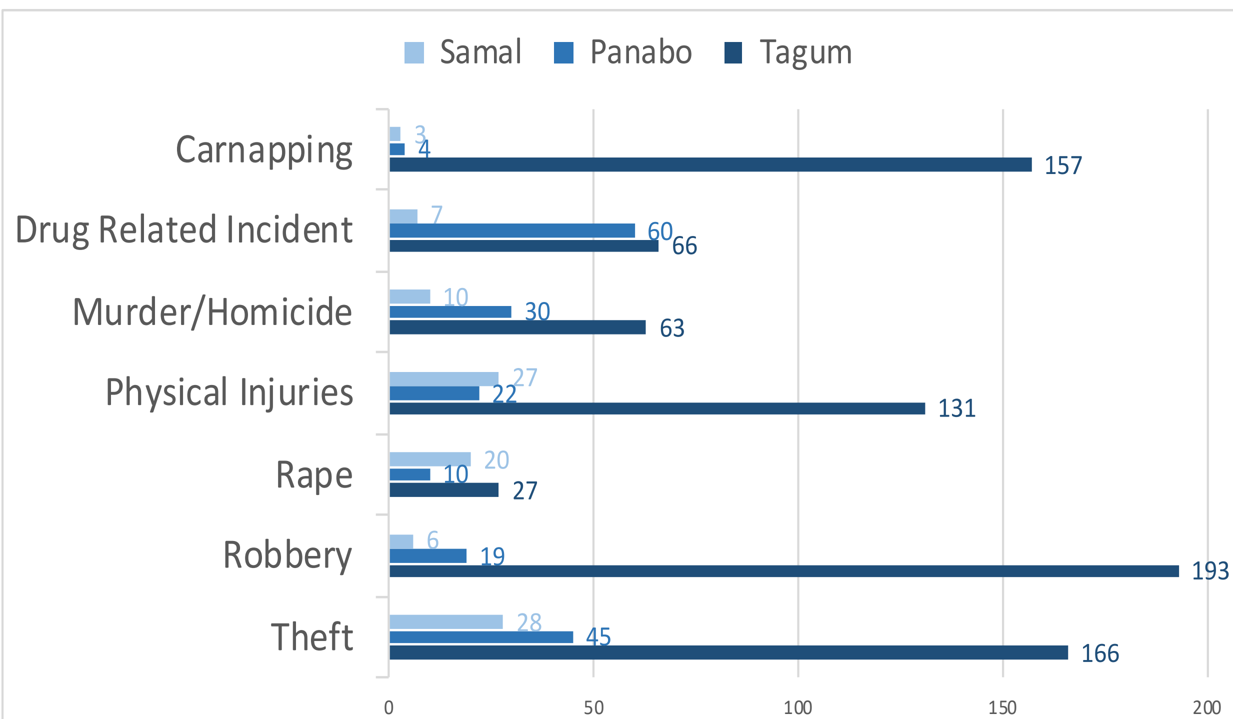


Figure 4.2 Crime Data Distribution by City

4.4.1 Random Forest Algorithm

The chosen algorithm to train the data for this project was Random Forest Classifier. This was due to the algorithm's features clearly described by Breiman and Cutler (2015). The ability to handle thousands of input variables, provide variable importance estimates, and handle unbalanced data sets are all attractive properties to achieve the objectives of the study. Random Forest's ability to provide estimates on variable importance is a good way to know how much each variable influence the probability outputs. Moreover, Random Forest extends the ability of a single standalone Decision Tree by generating multiple *random* Decision Trees to calculate the output of predictors. This attribute may reduce bias on the prediction outputs of the model especially with unbalanced data set without resampling. The Random Forest Classifier available within the Scikit Learn Python library was used to train and build the predictive model. Code 4.2 shows the function code for data training.

Code 4.2 Random Forest Classifier (RFC) Model Training Function

```
from sklearn.ensemble import RandomForestClassifier
def train_rfc_model(estimators, train_x, train_y):
    rfc = RandomForestClassifier(
        n_estimators=estimators,
        random_state=42
    )
    rfc.fit(train_x, train_y)
    return rfc
```

4.5 Model Evaluation

The evaluation of the model was executed by taking the accuracy, precision, recall, and F1 scores. These performance scores were measured using the Scikit Learn Metrics library. Code 4.3 shows the evaluation function code to generate metrics scores. The function accepts the trained model, test predictors, and test labels as parameters. Since the performance of Random Forest algorithm depends on the number of individual Decision Trees, different models were generated using different number of estimators. The performance of each model was evaluated to find the best model of the same training/testing data split.

Code 4.3 Evaluation Function

```
from sklearn.metrics import accuracy_score, precision_score, f1_score,
recall_score
import numpy as np

def evaluate_model(model, test_x, test_y):
    x=0
    print("{}, {}, {}, {}, {}, {}, {}".format('Estimators', 'Precision',
'F1', 'Recall', 'Accuracy', 'mean', 'std'))
    while x < 10:
        eval_score = model[x].predict(test_x)

        accuracy = accuracy_score(test_y, eval_score)
        precision_ave = precision_score(test_y, eval_score,
average='weighted')
        recall_ave = recall_score(test_y, eval_score, average='weighted')
        f1_ave = f1_score(test_y, eval_score, average='weighted')

        mean = np.median([accuracy*100, precision_ave*100, recall_ave*100,
f1_ave*100])
        std = np.std([accuracy*100, precision_ave*100, recall_ave*100,
f1_ave*100])

        print("{}, {:0.1f}, {:0.1f}, {:0.1f}, {:0.1f}, {:0.1f},
{:0.3f}".format(model[x].get_params()['n_estimators'], precision_ave*100,
f1_ave*100, recall_ave*100, accuracy*100, mean, std))
        x+=1
```

4.5.1 Initial Model

The initial model used the Tagum City crime data as the training data alone, without crime data from the other two cities. Since Tagum City has the highest number of crimes more than Panabo City and Samal City combined, as seen in Figure 4.2, it might have the capability to generalize the model. Test evaluation of the models was done with data from Panabo City and Samal City. Evaluation results are shown in Figure 4.3 and Figure 4.4 respectively.

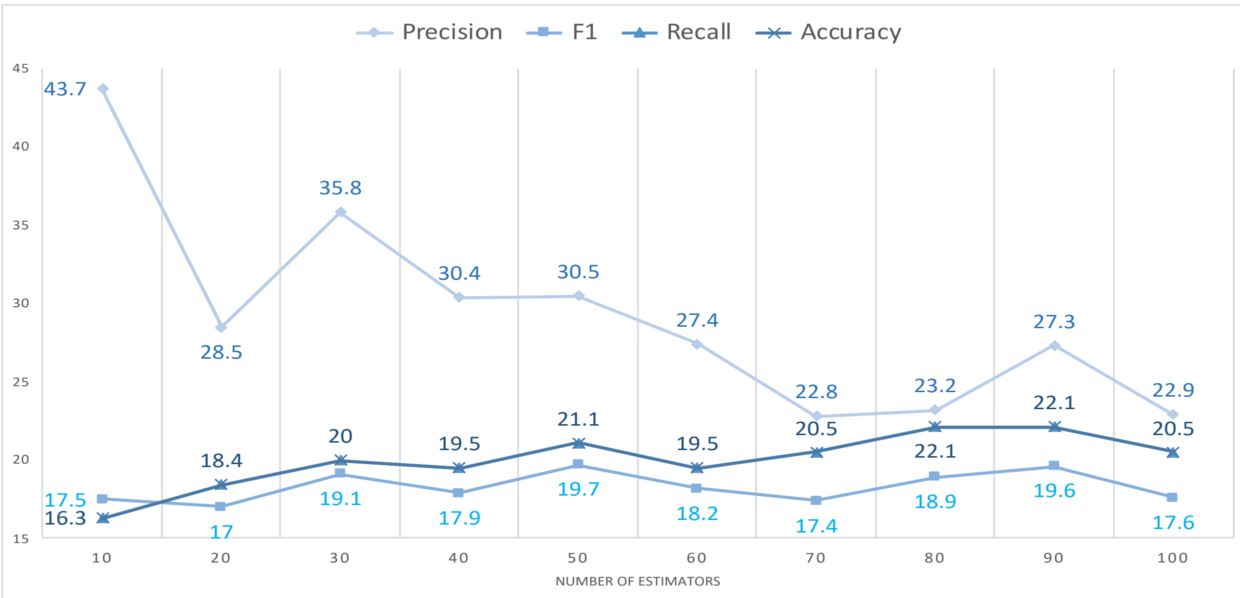


Figure 4.3 Initial Model Test Results with Panabo City Data

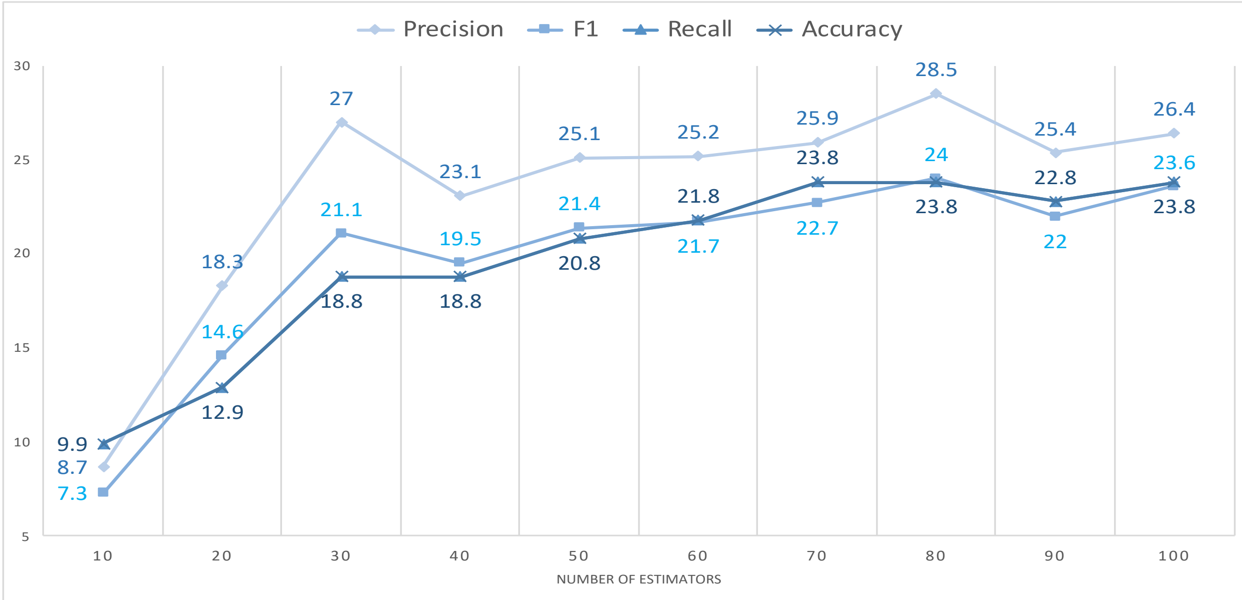


Figure 4.4 Initial Model Test Results with Samal City Data

Comparing Figure 4.3 and Figure 4.4, Tagum City training data does not seem to be a good generalization for the other two cities. This is apparent in the difference of the graph slopes. The number of estimators with best results is also different for the two cities. For Panabo City, 90 estimators is the best with mean result of 22.1 and standard deviation of 2.795. While for Samal City, the best results came from model with 80 estimators with mean result of 23.9 and standard deviation of 2.024.

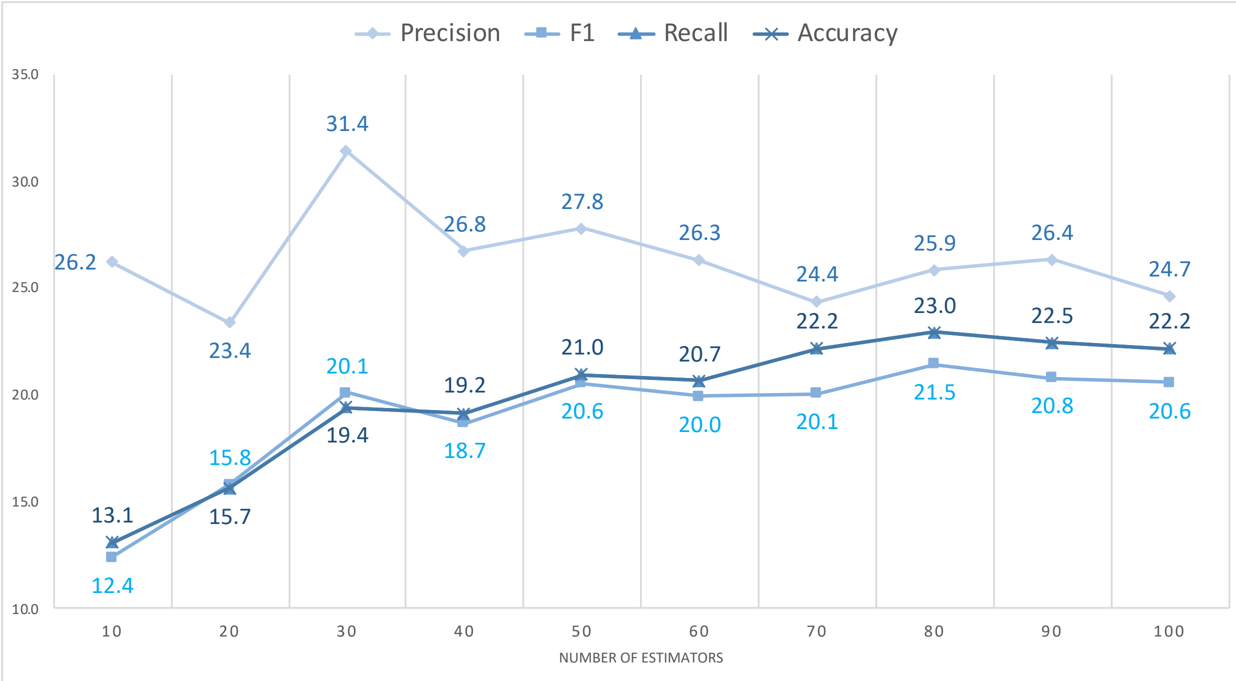


Figure 4.5 Initial Model Average Test Results

Combining the results of two cities together by getting their average has 80 numbers of estimators as seen in Figure 4.5. The best metrics has a mean of 23.3 with standard deviation of 1.841.

4.5.2 Stratified Model - All Data

Even though Tagum City crime data is significantly numerous, it does not reflect the crimes of Panabo City and Samal City. As an attempt to see how the model will perform using the whole crime data, another type of model was constructed. The model was trained using stratified data split of all crimes from the three cities. Code 4.4 shows the splitting of data into 75/25 training/testing ratio.

Code 4.4 Stratified Split Function

```
from sklearn.model_selection import train_test_split

def strat_data_split(data_model):
    X_train, X_test, y_train, y_test = train_test_split(
        data_model[independent_columns],
        data_model['crime_label'],
        random_state=42,
        shuffle=True,
        stratify=data_model['crime_label'])

    data_model_count = data_model['crime_label'].value_counts()
    train_count = y_train.value_counts()
    test_count = y_test.value_counts()

    print("{}, {}, {}, {}".format('crime','total','train','test'))

    counter = 0
    while counter < 7:
        print("{}, {}, {}, {}".format(crime_dict[counter],data_model_count[counter],train_count[counter],test_count[counter]))
        counter += 1

    print("{}, {}".format('X Train', X_train.shape))
    print("{}, {}".format('X Test', X_test.shape))
    print("{}, {}".format('y Train', y_train.shape))
    print("{}, {}".format('y Test', y_test.shape))
    return X_train, X_test, y_train, y_test
```

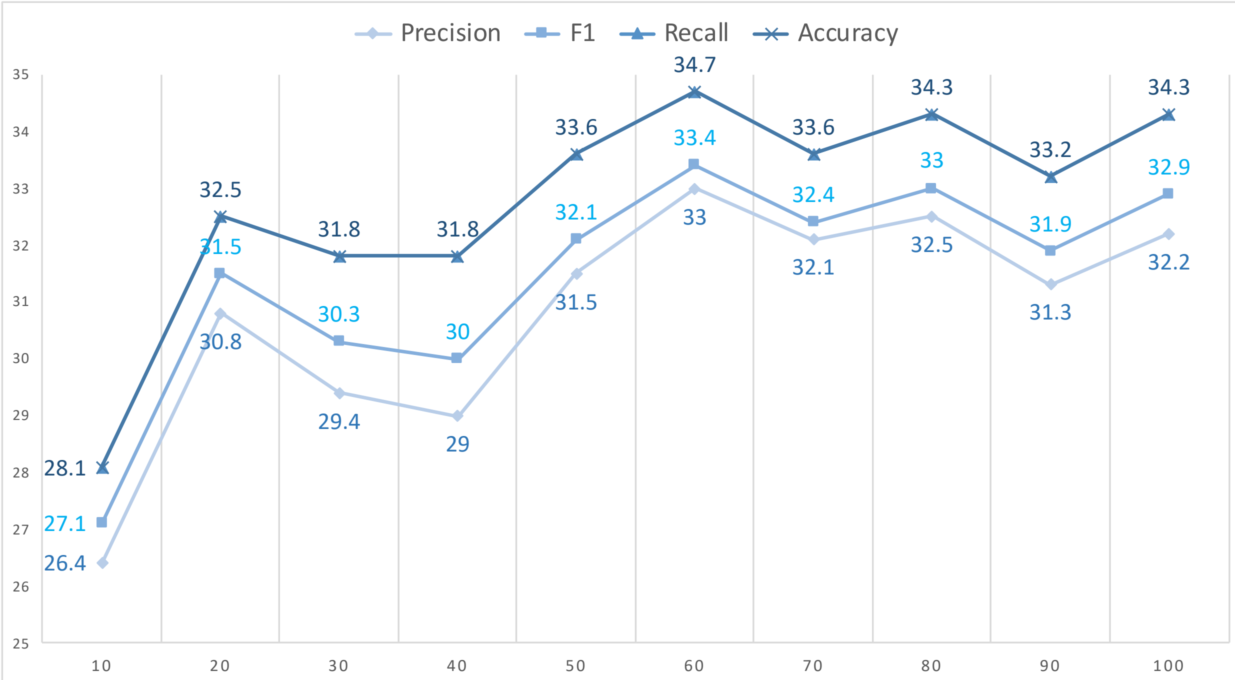


Figure 4.6 Stratified Model Test Results with All Crime Data

In the instance of using 75% of the whole data in training, the test result in Figure 4.6 does not have any similarities with the average results in the Figure 4.5 of the initial model in section 4.5.1. The best result of the stratification of all crime data has 60 numbers of estimators with metrics score mean of 34.1 and standard deviation of 0.729. This may mean that using a compilation of all crime data is still not a good model for all cities. Considering that the crime data is still dominantly Tagum City crime data, the risk calculations of this model may still be largely based on the Tagum City crime data. This creates bias against the two other cities with smaller data instances.

4.5.3 Stratified Model - By City

The results of past two model types do not produce desirable performance scores and neither has a good model generalization. In this respect, separate predictive crime model by city will be the best solution to address the bias of the model towards the city with the highest crime count. As shown on Figure 4.2, the most frequent type of crime differs among all three cities. This suggests that each city has its own type of crime model which further prove that a by-city predictive model is the most appropriate type of model to use for implementation.

In this section, several models were generated for each city using a stratified split crime data of the same city. After evaluation, the most important predictors of the best model of each city are identified using code on Code 4.5. The top influential predictors were then examined on their correlation to other input variables.

Code 4.5 Feature Importances Function

```
def get_important_features(model):
    importances = model.feature_importances_
    x=0
    for each in importances:
        print("{}$ {:0.2f}".format(independent_columns[x],each*100))
        x+=1
```

♦ ***Tagum City Model***. The stratified split distribution of Tagum City is shown on Figure 4.7. The most prominent crimes in Tagum City according to the data were theft, robbery, physical injuries, and carnapping. This may result in higher risk probabilities for these crime types.

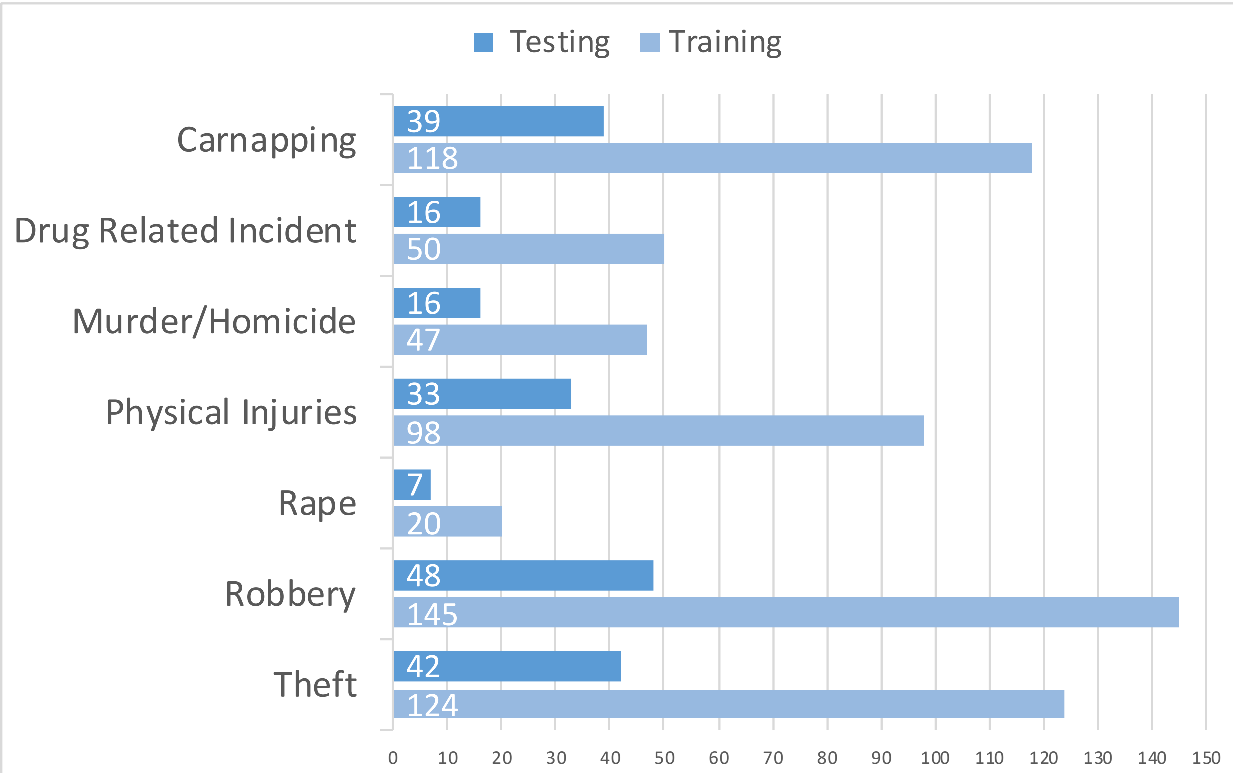


Figure 4.7 Stratified Split of Tagum City Crime Data

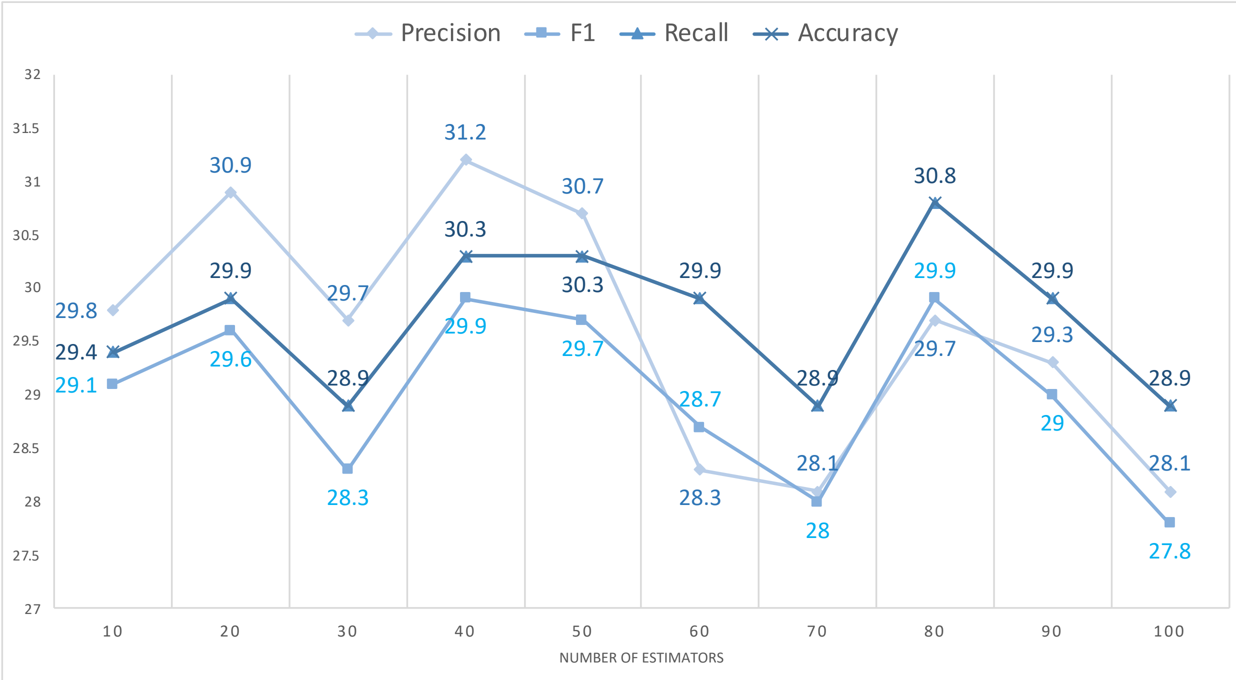


Figure 4.8 Stratified Model Test Results with Tagum City Crime Data

The best model of Tagum City model shown on Figure 4.8 has 40 numbers of estimators with 30.3 mean of all four metrics and a standard deviation of 0.474. The slope of performance on the graph does not seem to get better after 40 estimators. The metrics graph seems to have high fluctuations and has a trend of bouncing back and forth from the lower score of 28 to higher score of 31.

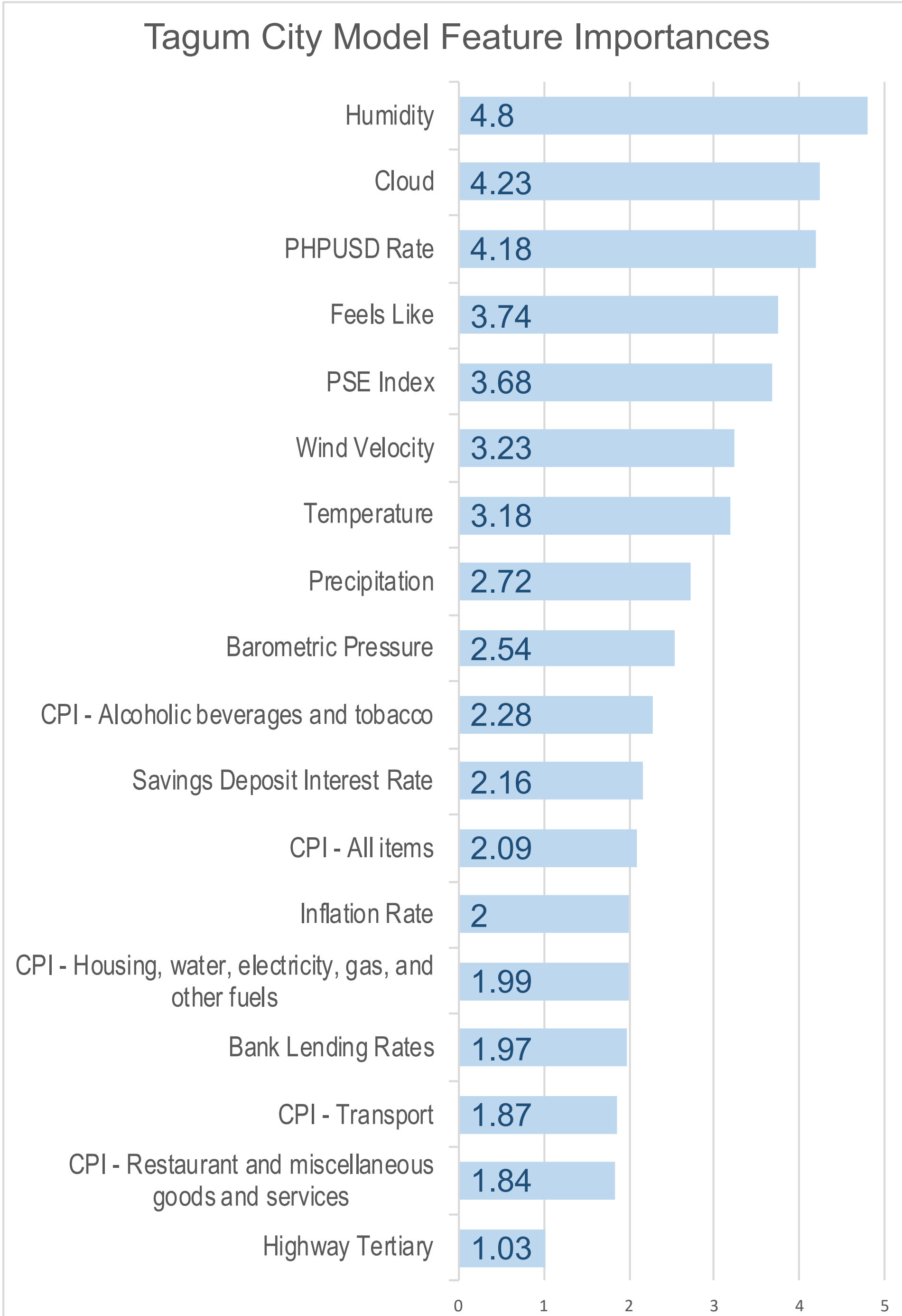
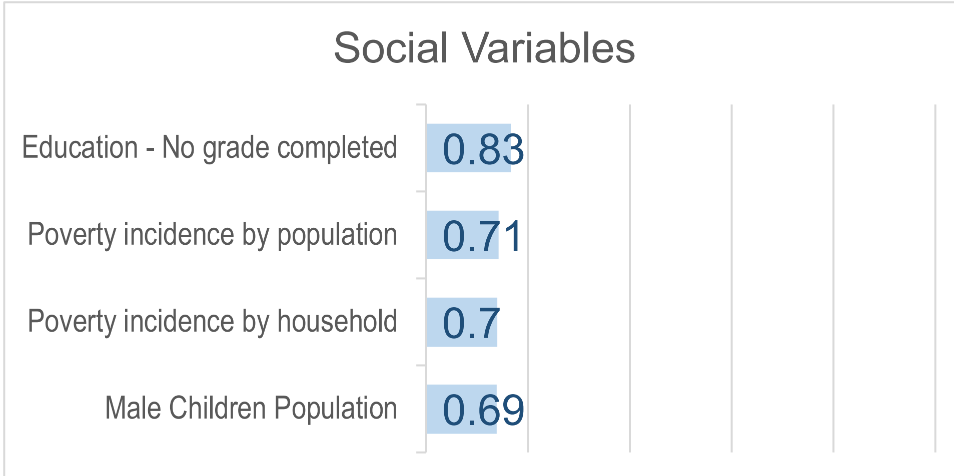
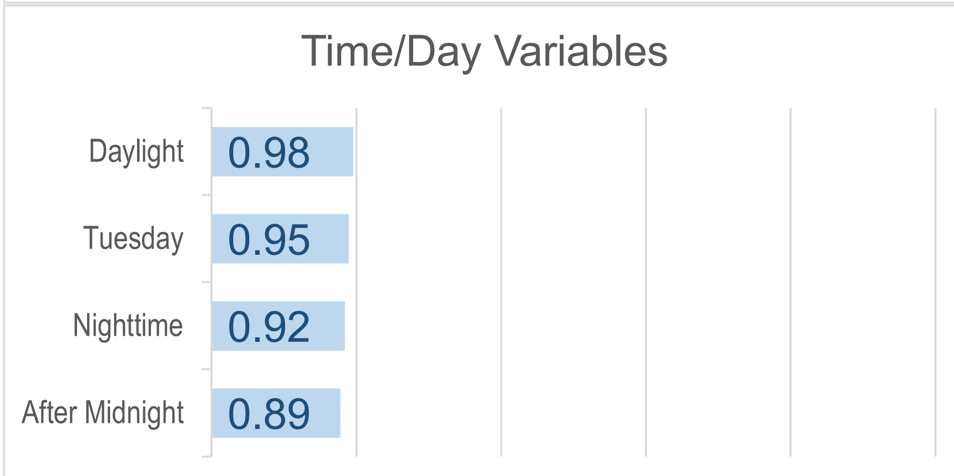
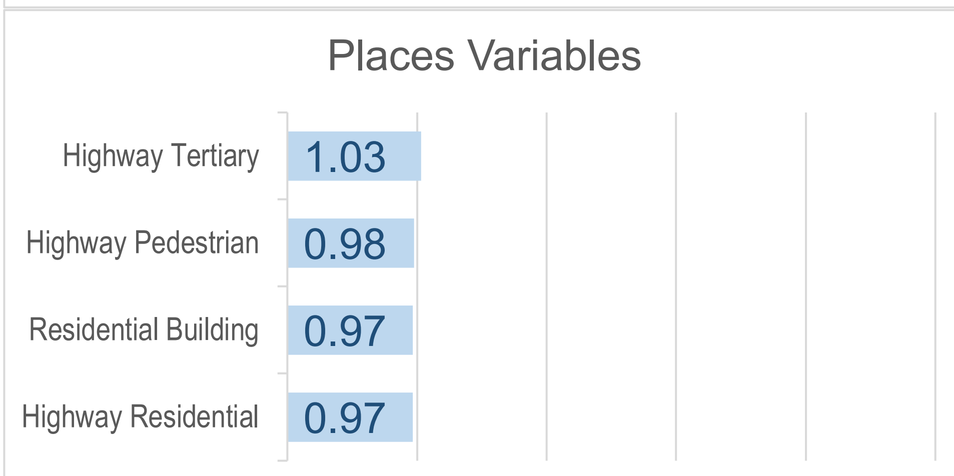


Figure 4.9 Tagum City Model Feature Importances

The most important features of Tagum City model with 40 estimators is illustrated in Figure 4.9. The top 18 out of 114 features include seven weather variables, ten economic variables, and one places variables. It is important to note that all economic variables are on the top most important for Tagum City model.


Social Variables
Education - No grade completed
0.83
Poverty incidence by population
0.71
Poverty incidence by household
0.7
Male Children Population
0.69


Time/Day Variables
Daylight
0.98
Tuesday
0.95
Nighttime
0.92
After Midnight
0.89


Places Variables
Highway Tertiary
1.03
Highway Pedestrian
0.98
Residential Building
0.97
Highway Residential
0.97

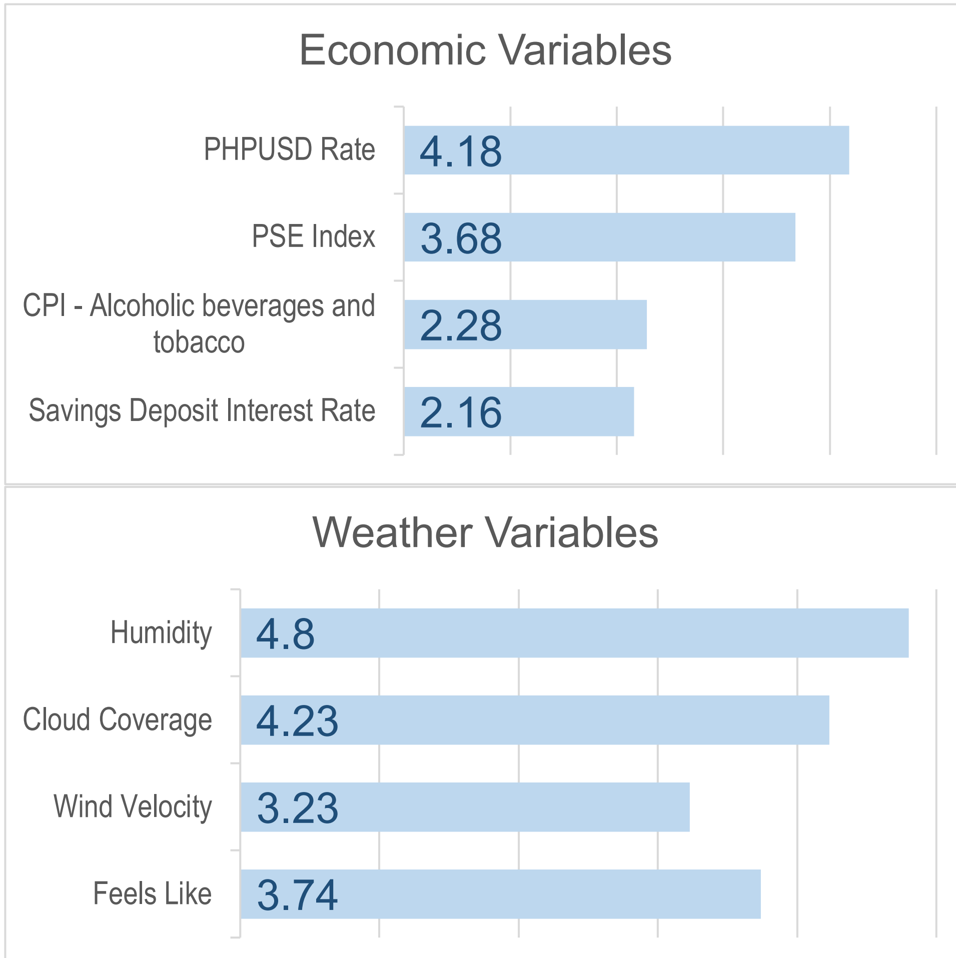


Figure 4.10 Tagum City Model Feature Importances - Top 4 Per Predictor Type

Figure 4.10 clearly shows all the top variables on each predictor type. The correlation of these variables to other variables was examined using *Pearson Correlation.*

	Highway Residential	*Residential Building*	*Early Morning*	*Place Type Urban*
Education - No grade completed	0.18	0.45	0.13	0.23
Poverty incidence by household	0.18	0.45	0.13	0.23
Poverty incidence by population	0.18	0.45	0.13	0.23
Male Children Population	0.18	0.45	0.13	0.23

Table 4.5 Tagum Social Variables Correlation

The most influential social variables are no education completed, poverty incidence by family and by individuals, and the male population of children. No educational background and poverty may logically contribute to the crime risk probabilities of a place. Since no educational achievement and poverty means the individual has lesser resources. The unusual result of having the number of male children on the top influential variables provokes an inquiry of how this may affect crime. This may be connected to the *street children* phenomenon in the Philippines and the result of Table 4.5 may mean that it posts as a security threat to society.

The social variables do not have strong positive or negative correlation with other variables except for those listed on Table 4.5. These variables all show a little more than expected association with residential highway, residential building, early morning, and urban variables.

	Temperature	*Feels Like*	*Wind Velocity*	*Humidity*	*Barometric Pressure*
After Midnight	-0.44	-0.47	-0.31	0.47	0.18
Tuesday	-0.02	0.00	0.08	0.04	-0.04
Daylight	0.59	0.62	0.29	-0.63	-0.04
Nighttime	-0.59	-0.62	-0.29	0.63	0.04

Table 4.6 Tagum Time/Day Variables Correlation

The most important time/day variables are after midnight, Tuesday, daylight, and nighttime. Except for Tuesday variable, all top variables are closely correlated with weather variables such as temperature, feels like, wind velocity, humidity, and barometric pressure. Correlations to other variables not mentioned here are expectedly low.

	Bank	*Bar*	*Commercial Building*	*Transport Terminal*	*Convenience Store*	*Gas Station*	*Greenfield*	*Hospital*
Highway Pedestrian	0.46	0.14	0.39	0.29	0.24	0.29	0.39	0.48
Highway Residential	0.05	0.00	0.26	0.10	-0.10	0.18	0.03	-0.04
Highway Tertiary	0.39	0.29	0.35	0.20	0.33	0.35	0.46	0.35
Residential Building	-0.19	-0.12	-0.06	-0.09	-0.20	-0.18	-0.29	-0.21
	Hotel	*Mall*	*Marketplace*	*Park*	*Pharmacy*	*Police Station*	*Restaurant*	*School*
Highway Pedestrian	0.20	0.34	0.39	0.33	0.38	0.18	0.37	0.28
Highway Residential	0.09	0.09	-0.03	-0.05	-0.08	-0.16	0.08	0.12
Highway Tertiary	0.29	0.32	0.30	0.28	0.30	0.15	0.45	0.31
Residential Building	0.00	-0.22	-0.12	-0.13	-0.20	-0.10	-0.14	0.00

Table 4.7 Tagum Places Variables Correlation

The Table 4.7 shows that top variables for places have many strong correlations with other places variables. Three out of four top places variables for Tagum City involve a type of highway; while the other one is a residential building. The presence of highways are positively correlated to the presence of bank, bar, commercial buildings, transport terminal, convenience store, gas station, greenfield, hospital, hotel, mall, marketplace, park, pharmacy, police station, restaurant, and school. Residential building is negatively associated with the mentioned places. Correlation of the top places variables to variables of other predictor types is expectedly low.

The presence of a highway in Tagum City is maybe significant to the risk calculation of crimes. Connecting the information from Figure 4.7, it may denote that the most numerous crimes such as carnapping, robbery, and theft, may happen on establishments along the busy highways or in residential areas.

	Temperature	*Humidity*	*Precipitation*	*Weather Clear*	*Weather Cloudy*	*Weather Rainy*
PHPUSD Rate	-0.16	-0.27	-0.12	-0.24	0.33	-0.20
PSE Index	-0.06	0.29	0.16	0.06	-0.22	0.23
CPI - Alcoholic beverages and tobacco	0.26	0.01	-0.06	0.34	-0.16	-0.11
Savings Deposit Interest Rate	-0.22	-0.19	-0.01	-0.26	0.21	-0.03

Table 4.8 Tagum Economic Variables Correlation

The most important economic variables are PHPUSD exchange rate, PSE index, Consumer Price Index of alcoholic drinks and tobacco, and savings deposit interest rate. Surprisingly, the economic variables are more strongly correlated to weather variables than to the other types of predictors. Currency exchange rate of Peso to US Dollar and savings deposit rate are both associated to cloudy weather; PSE index is associated to humidity and precipitation; while CPI of alcoholic beverages and tobacco are closely associated with temperature and clear weather. This result may be small evidence of how weather affects the economy.

	After Midnight	*After Work-Hours*	*Afternoon*	*Early Morning*	*Inflation Rate*	*Savings Deposit Interest Rate*
Feels Like	-0.47	0.36	0.56	-0.35	0.01	0.05
Wind Velocity	-0.31	0.28	0.26	-0.23	0.11	0.10
Cloud Coverage	0.00	0.19	-0.01	-0.16	0.10	0.06
Humidity	0.47	-0.30	-0.58	0.30	-0.20	-0.19

Table 4.9 Tagum Weather Variables Correlation

The most important weather variables are feels like, wind velocity, cloud, and humidity. These variables are expectedly correlated to time of the day and a little bit correlated to some economic variables. Humidity is correlated to hours after midnight and early morning hours. Cloud coverage is positively correlated to hours after work and inflation rate. Wind velocity and feels like are both correlated to hours after work and afternoon hours.

♦ ***Panabo City Model***. The stratified split of Panabo City data is illustrated in Figure 4.11. As observed, the crimes rape and carnapping have very little data. This may result in biases against the two crime types by having unusually low measure in risk probabilities. On the other hand, the most frequent crimes in Panabo City are theft, murder/homicide, physical injuries, and drug-related incidents.

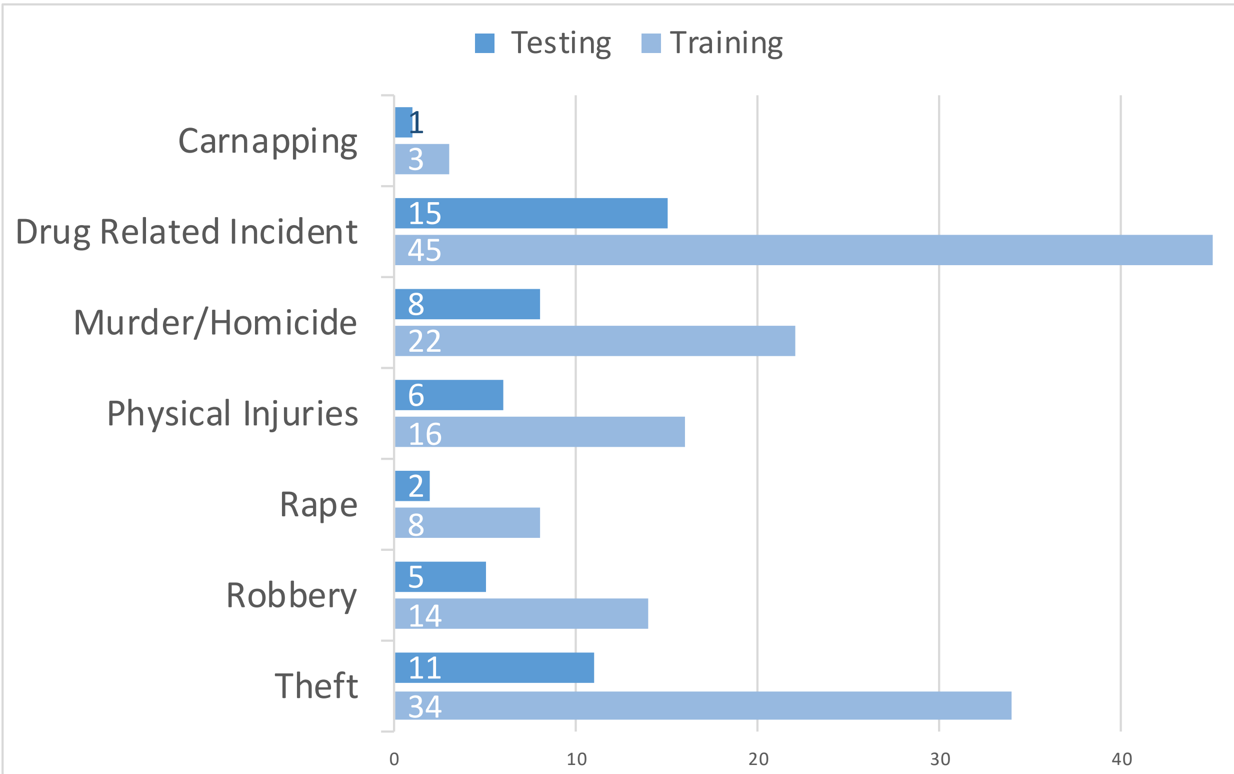


Figure 4.11 Stratified Split of Panabo City Crime Data

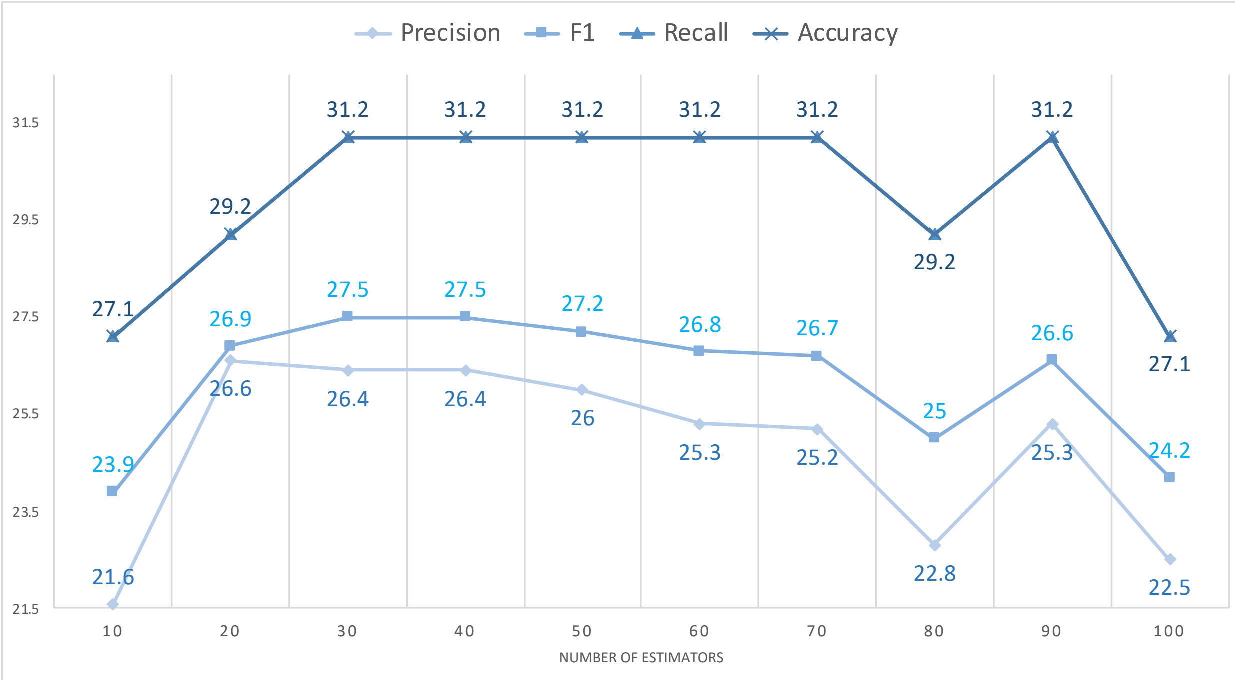


Figure 4.12 Stratified Model Test Results with Panabo City Crime Data

Matrix scores turns out to have big spreads for Panabo City data training results as seen on Figure 4.12. The best model has 30 estimators with mean of 29.4 and standard deviation of 2.168. After 30 estimators, the accuracy and recall are steady at the highest score of 31.2 but seems to fluctuate downward starting at 80 estimators. Precision and F1 scores have a sharp incline from 10 to 30 estimators, but gradually decline at 40 estimators.

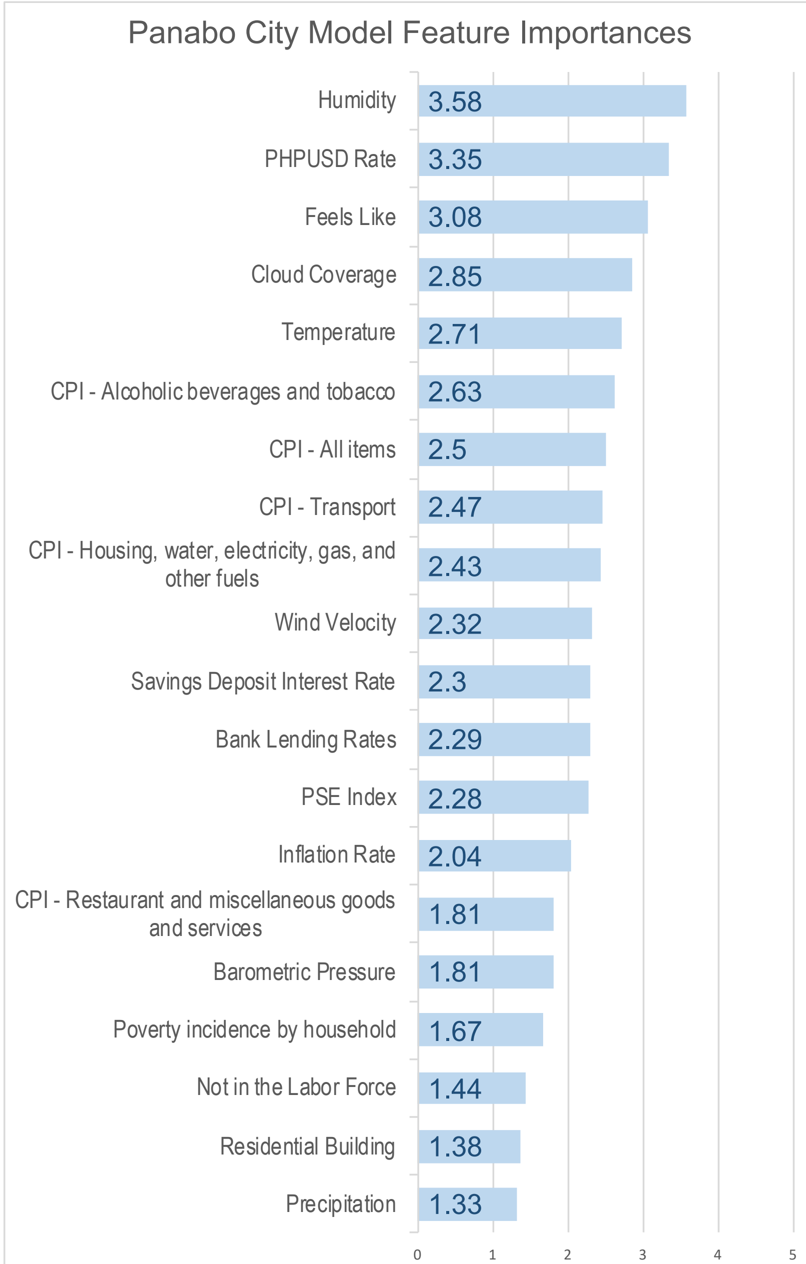
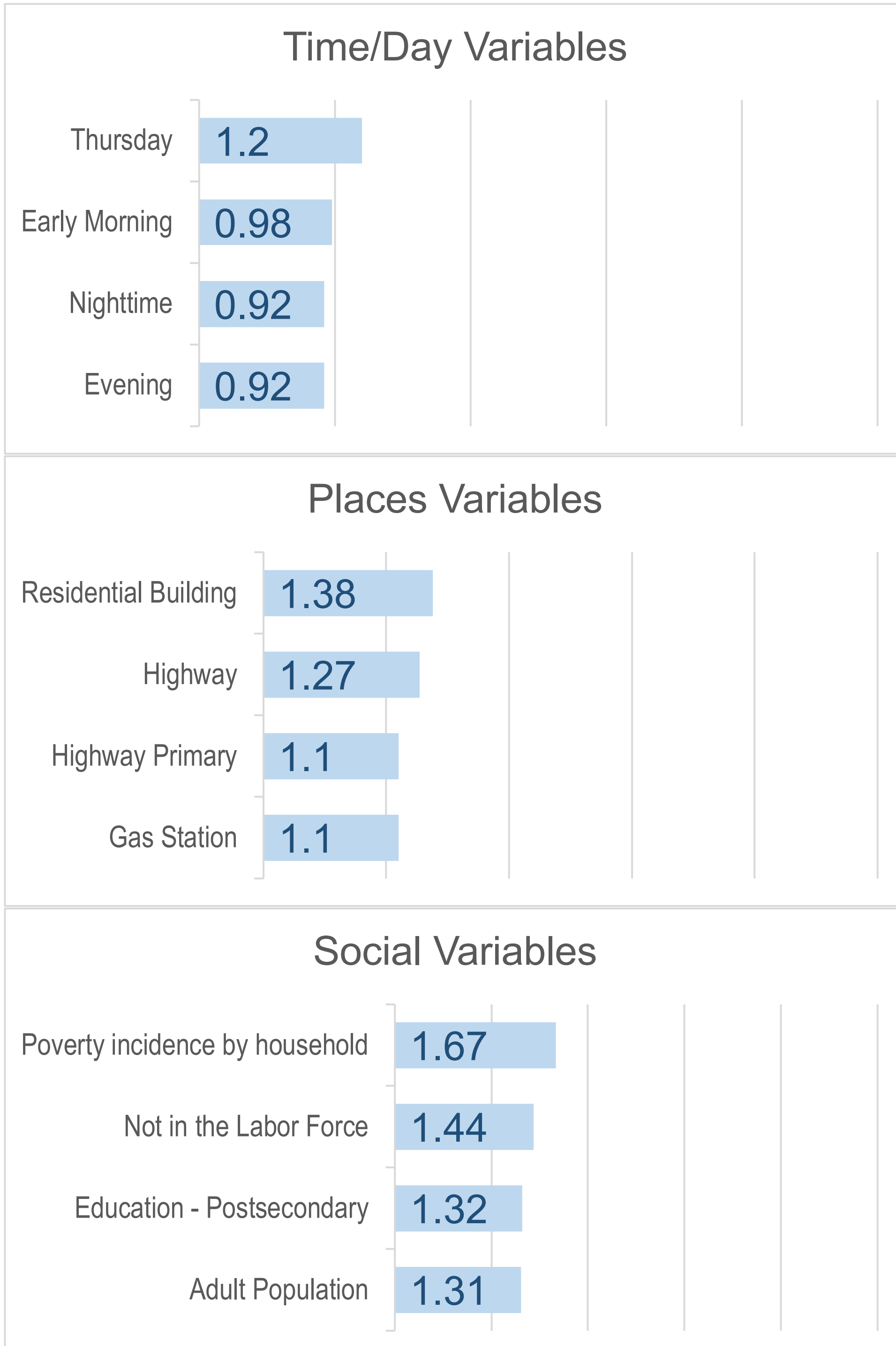


Figure 4.13 Panabo City Model Feature Importances

The most important features of Panabo City model with 30 estimators is illustrated in Figure 4.13. Like the feature importance result of Tagum City in Figure 4.9, the same weather and economic variables are also the top most important features for Panabo City mode. The order of importance, however, is not the same with Tagum City and Panabo City. The variables on top for Panabo City which are not present for Tagum City are residential building, poverty incidence by household, and number of people not in the labor force.


Time/Day Variables
Thursday
1.2
Early Morning
0.98
Nighttime
0.92
Evening
0.92
Places Variables
Residential Building
1.38
Highway
1.27
Highway Primary
1.1
Gas Station
1.1
Social Variables
Poverty incidence by household
1.67
Not in the Labor Force
1.44
Education - Postsecondary
1.32
Adult Population
1.31

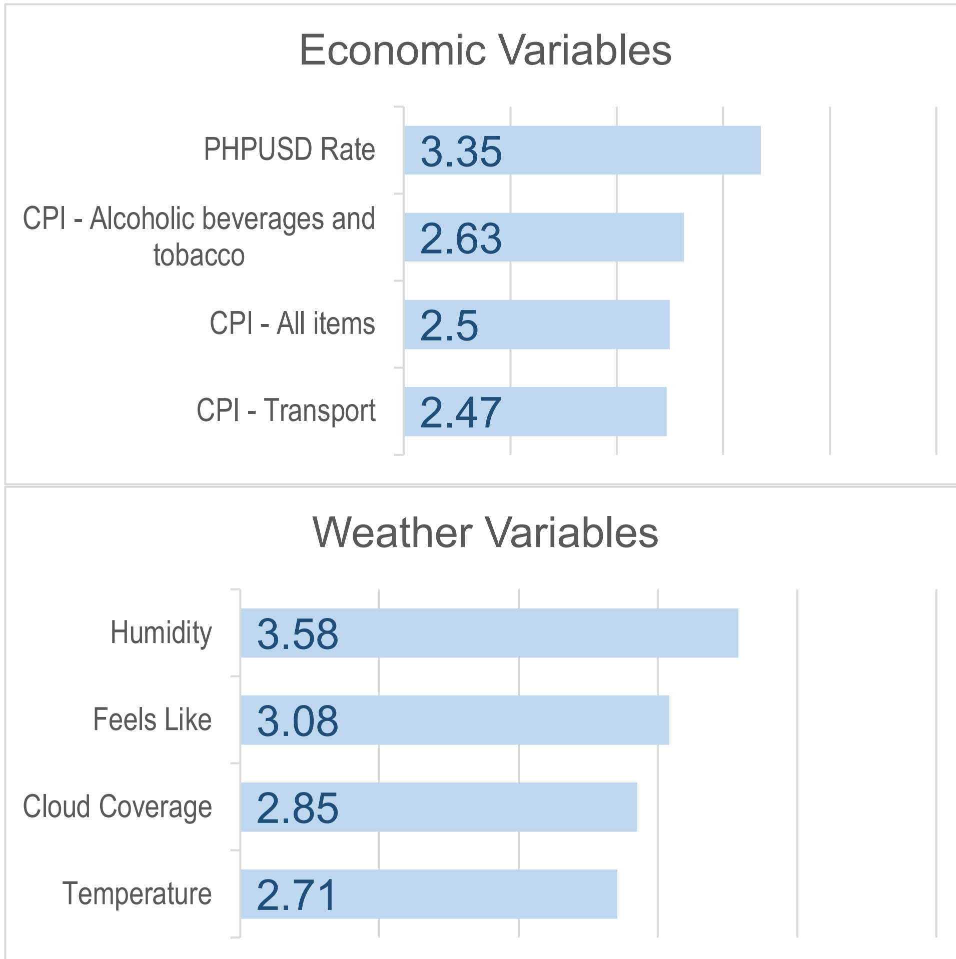


Figure 4.14 Panabo City Model Feature Importances - Top 4 Per Predictor Type

Figure 4.14 shows the top four variables in each type of predictors. The correlation of these variables to other variables was examined using *Pearson Correlation*.

	Cloud Coverage	*Humidity*	*Precipitation*	*Commercial Building*	*Highway Secondary*	*Highway Tertiary*	*Hospital*	*Park*
Early Morning	0.00	0.32	-0.12	0.12	0.10	0.14	0.15	0.18
Evening	0.20	0.44	0.21	0.13	-0.01	0.00	-0.04	-0.04
Thursday	-0.14	0.05	0.09	-0.07	-0.09	-0.10	-0.13	-0.08
Nighttime	0.11	0.64	0.19	0.17	0.08	-0.04	-0.05	-0.03

	Pharmacy	*Police Station*	*Residential Building*	*Restaurant*	*Tourist Attraction*	*PHPUSD Rate*	*PSE Index*	*Pawnshop*
Early Morning	0.10	0.10	0.07	0.19	0.11	0.13	-0.01	0.19
Evening	-0.14	-0.01	0.03	-0.08	0.02	0.00	0.03	-0.03
Thursday	-0.09	-0.13	0.16	-0.13	-0.06	0.07	-0.08	-0.07
Nighttime	-0.09	0.01	-0.06	-0.01	-0.05	-0.05	0.14	-0.01

Table 4.10 Panabo Time/Day Variables Correlation

The most important time/day variables shown on Table 4.10 are early morning, evening, Thursday, and nighttime. These variables are correlated with various types of predictors from weather, places, and economy. Early morning is correlated with humidity, commercial building secondary and tertiary highway, hospital, park, pharmacy, police station, restaurant, tourist attraction, PHPUSD rate, and pawnshop. Evening and nighttime variables are correlated to cloud, humidity, precipitation, and commercial building. Thursday is strangely correlated to residential building.

	Temperature	*Feels Like*	*Commercial Building*	*Monday*	*Weather Clear*	*Weather Cloudy*
PHPUSD Rate	-0.26	-0.10	-0.10	-0.20	-0.37	0.40
CPI - All items	0.29	0.20	0.15	0.23	0.49	-0.48
CPI - Alcoholic beverages and tobacco	0.28	0.21	0.16	0.23	0.43	-0.41
CPI - Transport	0.29	0.20	0.16	0.23	0.49	-0.48

Table 4.11 Panabo Economic Variables Correlation

Currency rate and three Consumer Price Index variables for all items, alcoholic beverages and tobacco, and transport are all top important economic variables as shown in Table 4.11. PHPUSD rate is positively correlated with cloudy weather; while all CPI variables are positively correlated with temperature, feels like, commercial building, Monday, and clear weather.

	Bank	*Bar*	*Bridge*	*Church*	*Commercial Building*	*Community Center*	*Convenience Store*	*Restaurant*	*School*
Gas Station	0.40	0.32	0.25	0.27	0.23	0.14	0.38	0.48	0.36
Highway	0.33	0.17	0.11	0.34	0.23	0.31	0.34	0.43	0.06
Highway Primary	0.18	0.56	0.35	0.15	0.08	0.14	0.20	0.09	0.21
Residential Building	-0.27	-0.12	-0.05	0.13	0.20	0.05	-0.11	-0.15	0.00
	Park	*Pawnshop*	*Pharmacy*	*Police Station*	*Hospital*	*Hotel*	*Mall*	*Marketplace*	*Transport Terminal*
Gas Station	0.11	0.26	0.32	0.15	0.46	0.02	0.57	0.71	0.13
Highway	0.24	0.27	0.22	0.31	0.19	0.05	-0.01	0.16	0.20
Highway Primary	-0.09	-0.09	-0.10	-0.12	-0.17	-0.09	-0.15	0.13	-0.07
Residential Building	0.02	-0.19	-0.20	-0.08	-0.12	0.31	-0.21	-0.22	0.15

Table 4.12 Panabo Places Variables Correlation

Table 4.12 shows the most important places variables for Panabo City. These variables are gas station, highway, primary highway, and residential building. Gas station is positively correlated to bank, bar, bridge, church, commercial building, community center, convenience store, restaurant, school, pawnshop, pharmacy, police station, hospital, mall, marketplace, and transport terminal. The presence of gas station in Panabo City seems close to important establishments where there are usually large numbers of people. This applies to highway and primary highway too. Residential building is positively correlated to commercial building, hotel, and transport terminal.

Since the most frequent crimes in Panabo City are theft, murder/homicide, physical injuries, and drug-related incidents, areas with large crowd may be a good indicator for a high crime risk place. Residential areas may also be used for drug-related operations where it can be privately hidden from the masses. This may be case since the presence of police station is negatively correlated with residential building. Meaning, most residences are usually far from police stations.

	Commercial Building	*Highway Residential*	*Hotel*	*Private Office*	*Residential Building*	*Road*	*Transport Terminal*	*Place Type Urban*
Education Postsecondary	0.30	0.39	0.13	0.23	0.43	0.17	0.11	0.52
Not in the Labor Force	0.30	0.39	0.13	0.23	0.43	0.17	0.11	0.52
Poverty incidence by household	0.30	0.39	0.13	0.23	0.43	0.17	0.11	0.52
Adult Population	0.30	0.39	0.13	0.23	0.43	0.17	0.11	0.52

Table 4.13 Panabo Social Variables Correlation

The most important social variables for Panabo City shown in Table 4.13 are postsecondary education, population not in the labor force, poverty incidence, and adult population. These social factors seem to influence the crime risk probabilities more than other social variables. These top social variables are all positively correlated to commercial building, residential highway, hotel, private office, residential building, road, transport terminal, and urban place.

	Mall	*CPI All items*	*CPI Alcoholic beverages and tobacco*	*CPI Transport*	*CPI Housing, water, electricity, gas, and other fuels*	*After Work-Hours*	*Afternoon*	*Friday*
Temperature	0.11	0.29	0.28	0.29	0.28	0.32	0.39	0.11
Feels Like	0.11	0.20	0.21	0.20	0.20	0.41	0.43	0.17
Cloud Coverage	0.02	-0.19	-0.17	-0.19	-0.18	0.02	-0.08	0.21
Humidity	-0.16	0.01	-0.02	0.01	0.01	-0.42	-0.49	-0.21

Table 4.14 Panabo Weather Variables Correlation

The most important weather variables, as shown on Table 4.14, are temperature, feels like, cloud coverage, and humidity. Temperature and feels like are correlated to mall, CPI variables, after-work hours, afternoon, and Friday. Cloud coverage is positively correlated to Friday; while humidity is negatively correlated to after-work hours, afternoon, and Friday. Humidity does not have strong positive correlation with other variables.

♦ ***Samal City Model***. This city has the lowest count of crime data at only 101 crime instances. Figure 4.15 shows that robbery, murder/homicide, drug-related incidents, and carnapping have very few data samples for training and testing. Because of this, risk calculations for these crimes may be very low. The most reported crimes in Samal City are theft, rape, and physical injuries.

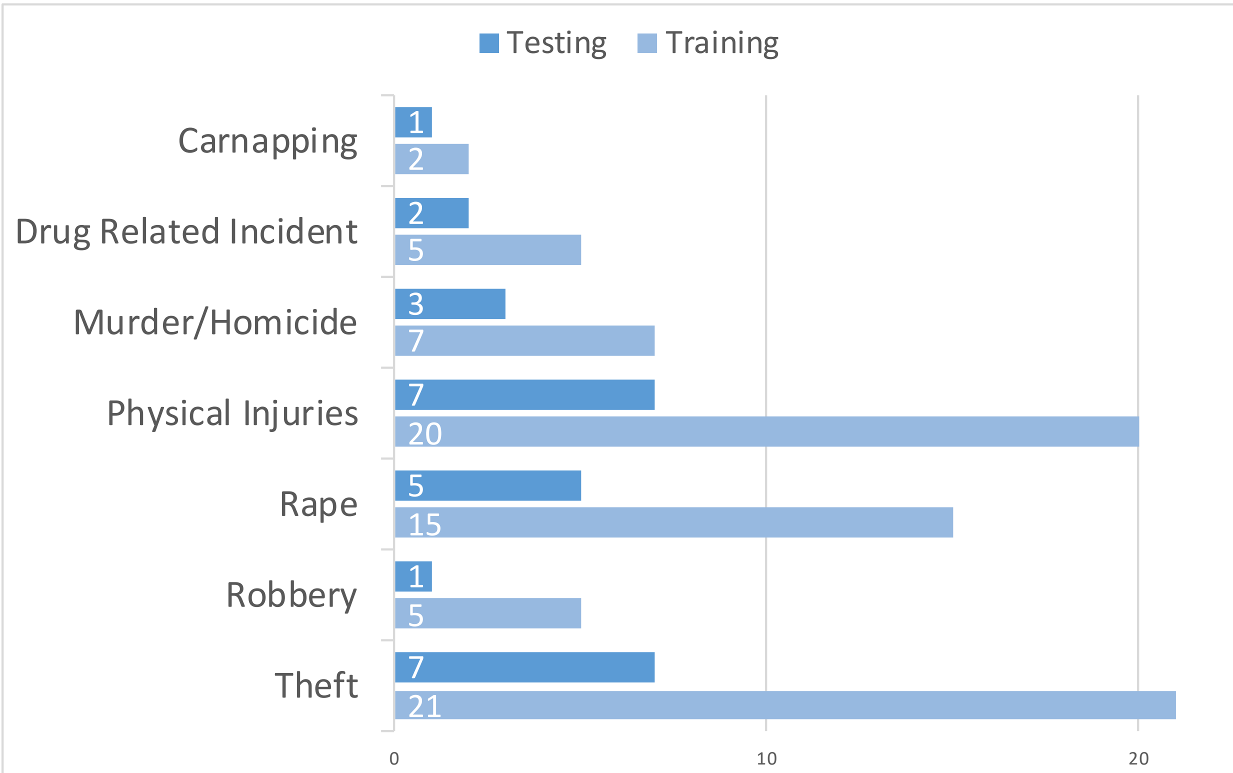


Figure 4.15 Stratified Split of Samal City Crime Data

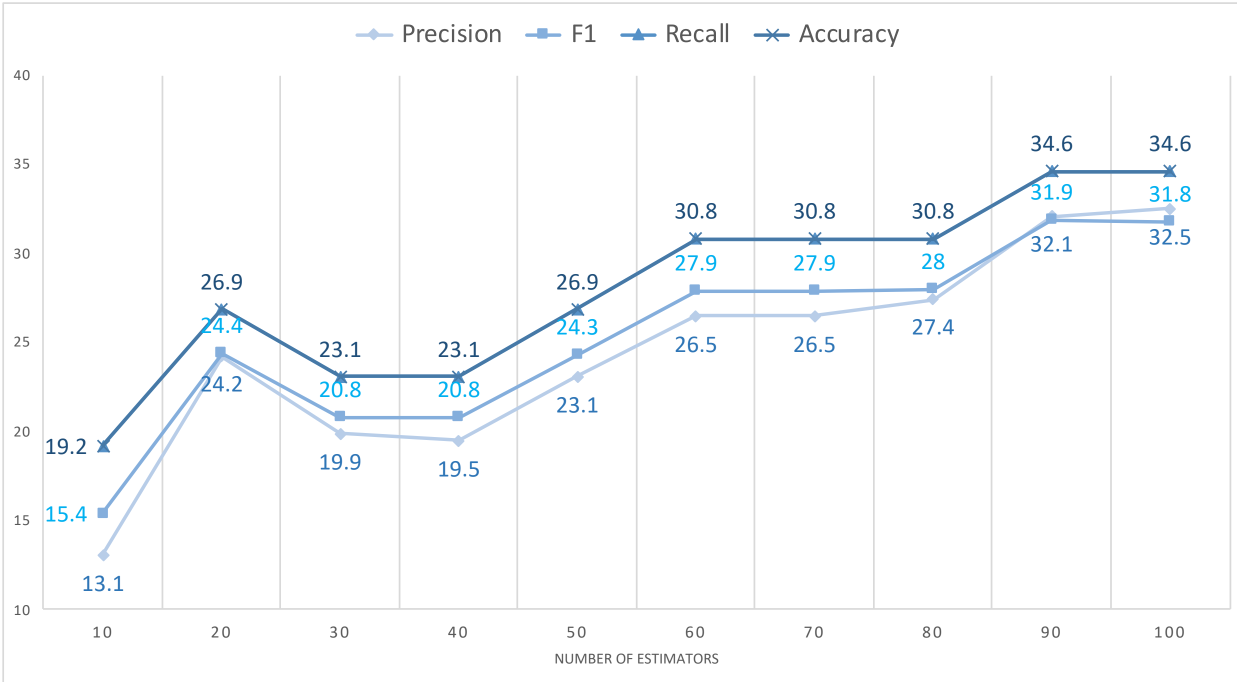


Figure 4.16 Stratified Model Test Results with Samal City Crime Data

Unlike the previous metric graphs of Tagum City and Panabo City, the metric performance of Samal City has an upward trend from 10 to 100 numbers of estimators. This results in a beautiful performance slope drawn on the graph as shown in Figure 4.16. The best model generated for Samal City has 100 estimators with mean score of 33.6 and standard deviation of 1.246.

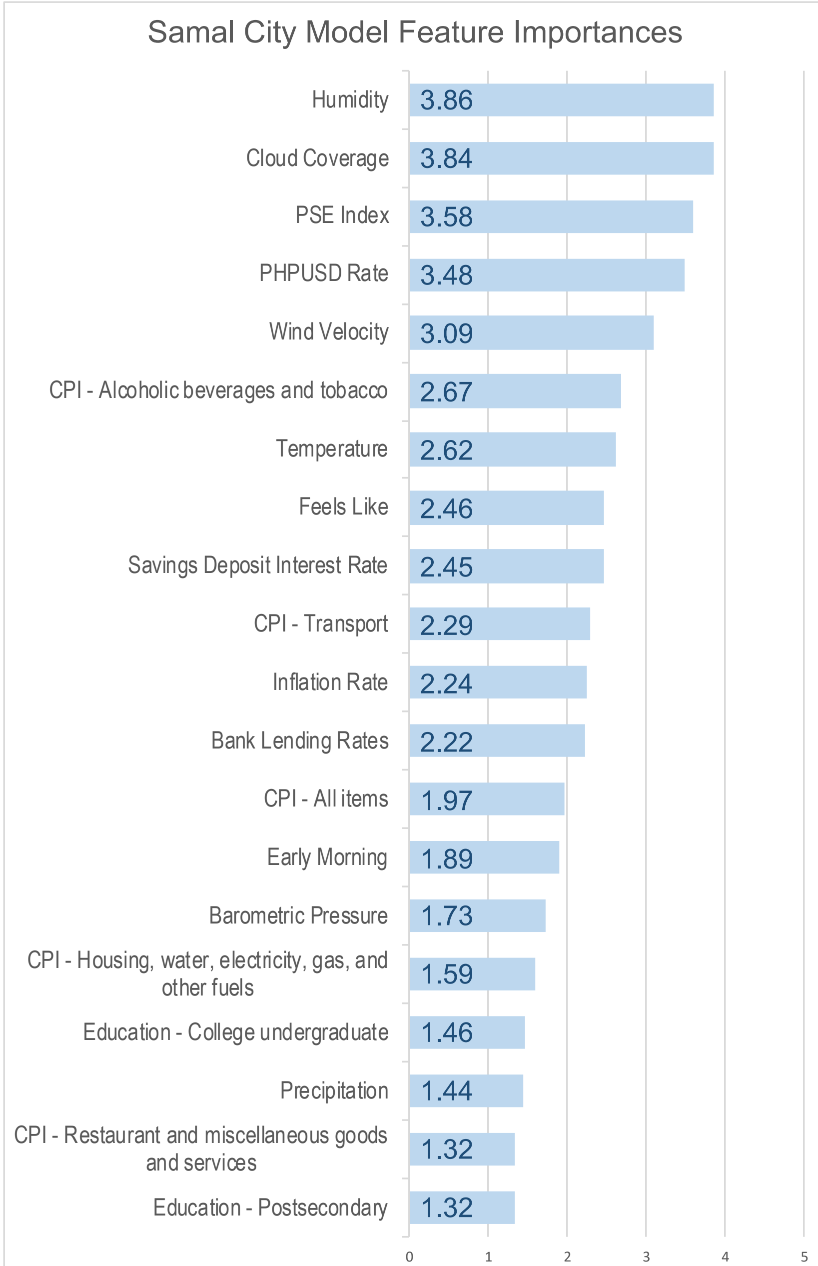
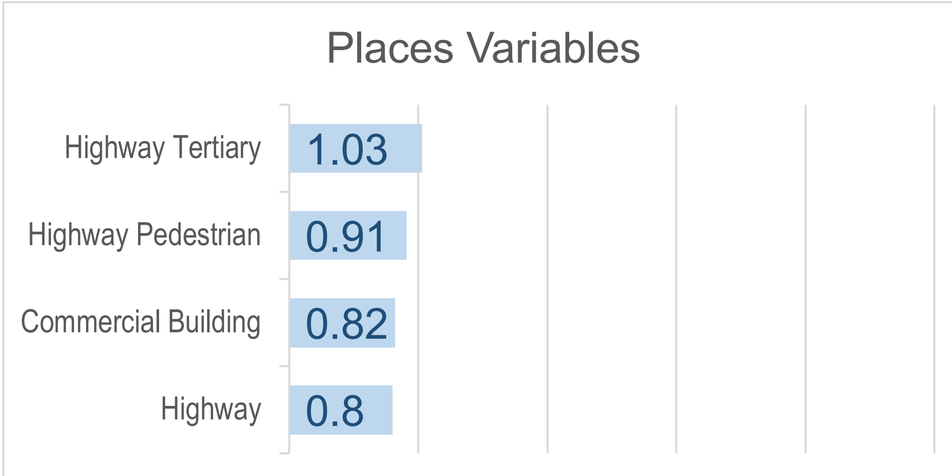
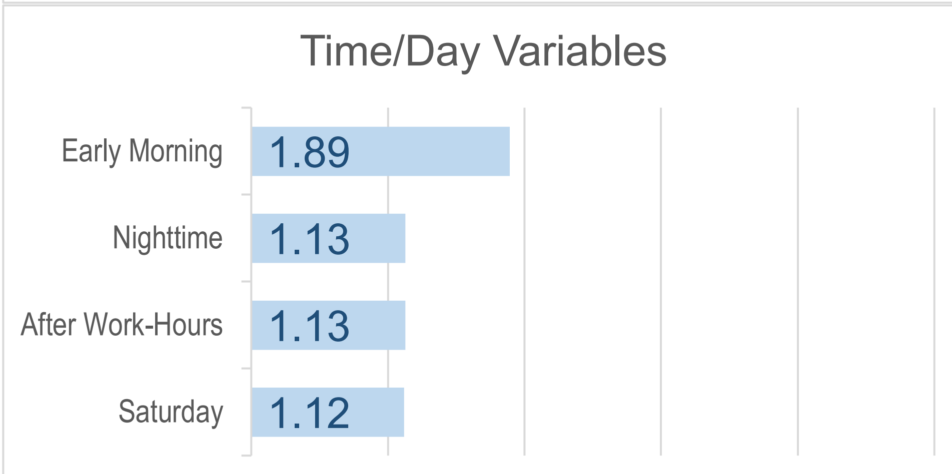
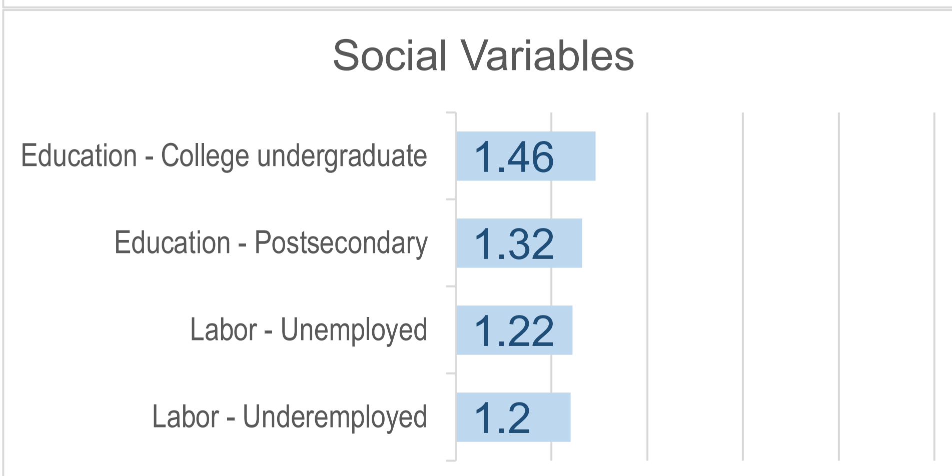


Figure 4.17 Samal City Model Feature Importances

The most important features of Samal City model with 100 estimators is illustrated in Figure 4.17. The same weather variables and all economic variables from Tagum City and Panabo City feature importances are also at the top 20 most important predictors for Samal City. The unique variables for Samal City on the top most variables are early morning, number of population who have college undergraduate education, and number of population who have completed postsecondary education.


Places Variables
Highway Tertiary
1.03
Highway Pedestrian
0.91
Commercial Building
0.82
Highway
0.8


Time/Day Variables
Early Morning
1.89
Nighttime
1.13
After Work-Hours
1.13
Saturday
1.12


Social Variables
Education - College undergraduate
1.46
Education - Postsecondary
1.32
Labor - Unemployed
1.22
Labor - Underemployed
1.2

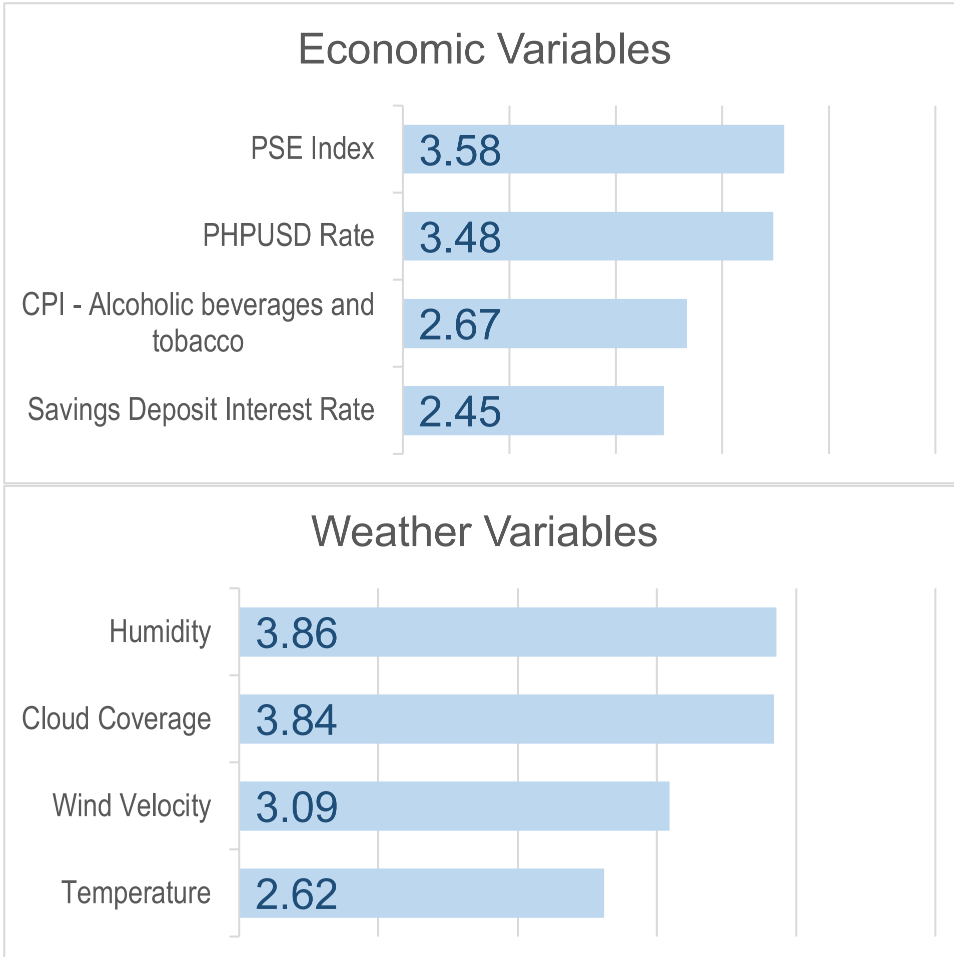


Figure 4.18 Samal City Model Feature Importances - Top 4 Per Predictor Type

Figure 4.18 shows the top four most important in every predictor type. The correlation of these variables to other variables was examined using *Pearson Correlation.*

	Humidity	*Precipitation*	*Barometric Pressure*	*Bank*	*Bar*	*Beach*
Commercial Building	0.14	0.12	0.16	0.26	0.18	0.43
Highway	0.06	0.02	0.08	0.18	-0.08	0.00
Highway Pedestrian	0.18	0.14	0.11	0.31	0.21	0.52
Highway Tertiary	0.05	-0.10	0.08	0.17	0.12	0.09

	Church	*Community Center*	*Convenience Store*	*Gas Station*	*Government Office*	*Greenfield*
Commercial Building	0.50	0.37	0.19	0.53	0.37	0.13
Highway	0.00	0.26	0.07	0.08	0.07	0.15
Highway Pedestrian	0.67	0.30	0.34	0.63	0.06	-0.09
Highway Tertiary	0.15	0.24	0.27	0.25	0.27	0.13

	Pharmacy	*Police Station*	*Residential Building*	*Restaurant*	*Road*	*School*
Commercial Building	0.18	0.32	0.40	0.45	0.32	0.50
Highway	-0.02	0.10	0.15	-0.08	0.02	0.01
Highway Pedestrian	0.38	0.38	0.19	0.63	0.38	0.61
Highway Tertiary	0.20	0.20	0.29	0.04	0.24	0.15

	Transport Terminal	*PHPUSD Rate*	*Inflation rate*	*Savings Deposit Interest rate*	*After Midnight*	*Early Morning*
Commercial Building	0.42	0.19	0.23	0.16	0.00	0.17
Highway	-0.09	0.10	0.13	0.09	0.28	-0.05
Highway Pedestrian	0.49	0.22	0.25	0.19	0.02	0.24
Highway Tertiary	0.27	0.10	0.16	0.12	0.23	-0.19

Table 4.15 Samal Places Variables Correlation

The top places variables for Samal City shown in Table 4.15 are surprisingly correlated to a number of different variables. Commercial building and three types of highways are very important to the crime risk model. Commercial building is strongly correlated to beach, gas station, restaurant, school, transport terminal, police station, and residential building. This may mean that theft, rape, and physical injuries usually happen within establishments close to the vicinity of a commercial building. Samal City is known for its beach resorts for leisure activities. Interactions between individuals are particularly centered over food and alcoholic drinks, and this may explain why rape and physical injuries are the main crimes in the city.

	Bank	*Bridge*	*Cemetery*	*Church*	*Commercial Building*	*Community Center*	*Convenience Store*	*Fire Station*	*Gas Station*
Education College undergraduate	0.18	0.24	0.34	0.49	0.47	0.40	0.20	0.24	0.47
Education Postsecondary	0.18	0.24	0.34	0.49	0.48	0.40	0.20	0.24	0.46
Labor Underemployed	0.18	0.24	0.34	0.49	0.47	0.40	0.20	0.24	0.47
Labor Unemployed	0.18	0.24	0.34	0.49	0.47	0.40	0.20	0.24	0.47
	Government Office	*Greenfield*	*Highway*	*Highway Pedestrian*	*Highway Primary*	*Highway Residential*	*Highway Secondary*	*Highway Tertiary*	*Marketplace*
Education College undergraduate	0.23	0.40	0.28	0.43	0.24	0.52	0.28	0.35	0.36
Education Postsecondary	0.23	0.40	0.27	0.43	0.24	0.52	0.28	0.34	0.36
Labor Underemployed	0.23	0.40	0.28	0.43	0.24	0.52	0.28	0.35	0.36
Labor Unemployed	0.23	0.40	0.28	0.43	0.24	0.52	0.28	0.35	0.36
	Park	*Pharmacy*	*Police Station*	*Residential Building*	*Restaurant*	*Road*	*School*	*Inflation rate*	*Bank lending rates*
Education College undergraduate	0.17	0.28	0.22	0.25	0.50	0.31	0.44	0.15	0.12
Education Postsecondary	0.17	0.28	0.22	0.25	0.50	0.31	0.44	0.15	0.12
Labor Underemployed	0.17	0.28	0.22	0.25	0.50	0.31	0.44	0.15	0.12
Labor Unemployed	0.17	0.28	0.22	0.25	0.50	0.31	0.44	0.15	0.12

Table 4.16 Samal Social Variables Correlation

The most important social variables for Samal City shown in Table 4.16 are two education variables, college undergraduate, and two labor variables, underemployed and unemployed. All these variables are positively correlated to 25 places and two economic variables.

Education and labor seems to strongly influence crime in Samal City. Lessening the values of these variables may lessen the crime risk measurements of the area.

	Bar	*Clinic*	*Convenience Store*	*Highway Pedestrian*	*Restaurant*	*PHPUSD Rate*	*Place Type Rural*
After Work-Hours	-0.05	0.32	-0.07	-0.13	-0.16	0.21	0.22
Early Morning	0.24	-0.07	0.08	0.24	0.29	-0.07	-0.13
Saturday	-0.04	0.11	0.22	0.05	0.11	-0.09	-0.09
Nighttime	-0.13	-0.11	-0.16	0.03	-0.01	0.03	-0.09

Table 4.17 Samal Time/Day Variables Correlation

Important time/day variables are shown in Table 4.17. These variables are after-work hours, early morning, Saturday, and nighttime. After-work hours are correlated with clinic, PHPUSD rate, and rural areas. Early morning is correlated with bar, pedestrian highway, and restaurant. Saturday is positively correlated to clinic, convenience store, and restaurant; while nighttime is negatively correlated to bar and convenience store. The nighttime result is odd since bars and convenience stores operate at night, however, this may mean that there are not many bars and convenience stores in Samal City.

	Restaurant	*School*	*Monday*	*Weather Clear*	*Weather Rainy*
PHPUSD Rate	0.24	0.19	-0.39	-0.17	0.22
PSE Index	-0.16	-0.16	0.24	0.16	-0.19
CPI - Alcoholic beverages and tobacco	-0.08	-0.01	0.25	0.28	-0.06
Savings Deposit Interest Rate	0.30	0.26	-0.30	-0.24	0.24

Table 4.18 Samal Economic Variables Correlation

PHPUSD rate, PSE index, CPI of alcoholic beverages and tobacco, and savings deposit interest rate are the most important economic variables for Samal City shown in Table 4.18. The economic variables are correlated to weather and places variables. PHPUSD rate and savings deposit interest rate are correlated, surprisingly, to restaurant, school, and rainy weather. PSE index and CPI of alcoholic drinks and tobacco are correlated to Monday and clear weather.

	CPI - All items	CPI - Alcoholic beverages and tobacco	CPI - Transport	CPI - Housing, water, electricity, gas, and other fuels	CPI - Restaurant and miscellaneous goods and services	Inflation Rate	Savings Deposit Interest Rate	Bank Lending Rates
Temperature	0.35	0.37	0.35	0.34	0.36	-0.29	-0.21	-0.07
Wind Velocity	-0.14	-0.14	-0.14	-0.15	-0.16	0.00	-0.02	-0.03
Cloud Coverage	-0.29	-0.25	-0.29	-0.27	-0.27	0.38	0.39	0.31
Humidity	-0.08	-0.13	-0.08	-0.08	-0.10	0.00	0.01	-0.08

Table 4.19 Samal Weather Variables Correlation

The most important weather variables of Samal City model are all correlated to economic variables as shown on Table 4.19. Temperature is positively correlated to all CPI variables; while wind velocity, cloud coverage, and humidity are all negatively correlated to all CPI variables. Temperature is also negatively correlated to inflation rate, savings deposit interest rate, and bank lending rates; while cloud is positively correlated to the mentioned rate variables.

4.5.4 Key Features

In all cities, the two types of predictors consistently on the top most of feature importance are weather and economic variables. Among all weather variables, humidity and cloud are in the top two most of the time. The same is true with PHPUSD rate, PSE index, and CPI of alcoholic drinks and tobacco from the economic variables. The most common top social predictor is poverty incidence by household. The most important places are observed to be residential building and highway. While the most common important time/day variables are nighttime and early morning. The following figures show all mentioned key variables by crime incidence.

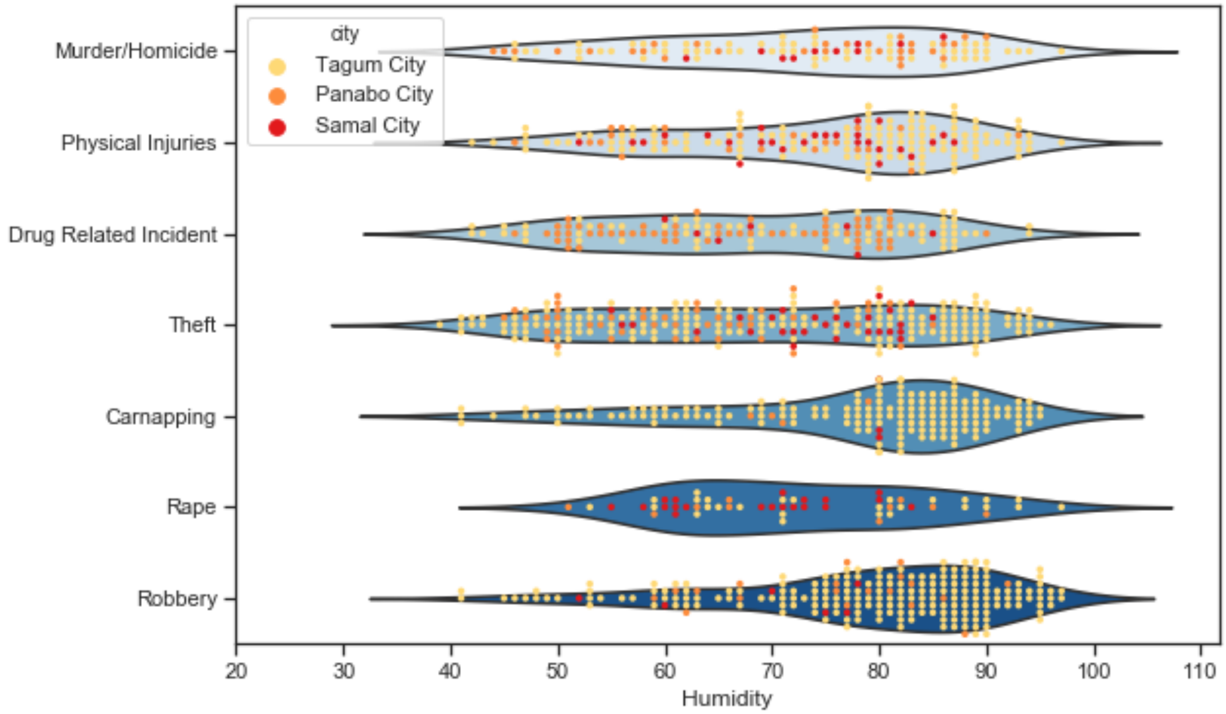


Figure 4.19 Crime Incidence by Humidity

Plotting the values of crime incidences against humidity values in Figure 4.19 shows some pattern. It can be observed that physical injuries, carnapping, and theft mostly happen when humidity value is between the ranges of 85 to 95. Robbery happens mostly when humidity is between the ranges of 70 to 100; while murder/homicide, rape, and drug-related incidents seems evenly distributed from 40 to 100.

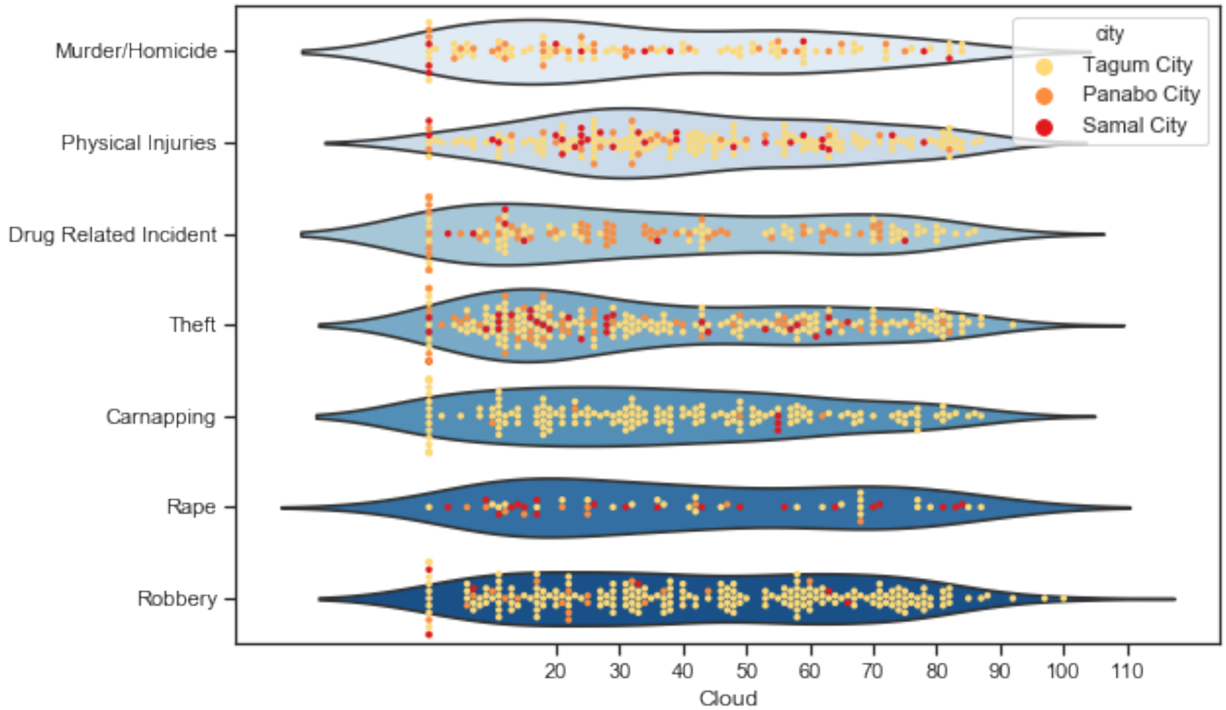


Figure 4.20 Crime Incidence by Cloud Coverage

In Figure 4.20, it can be observed that carnapping, theft, robbery, and drug-related incidents happen mostly when cloud coverage is zero. While carnapping and theft crimes tend to happen when the sky is cloudless or up to 30% coverage, it can be observed that all other types of crime seems evenly distributed from 0 to 100. This means that most crimes happen when there is low chance of rain.

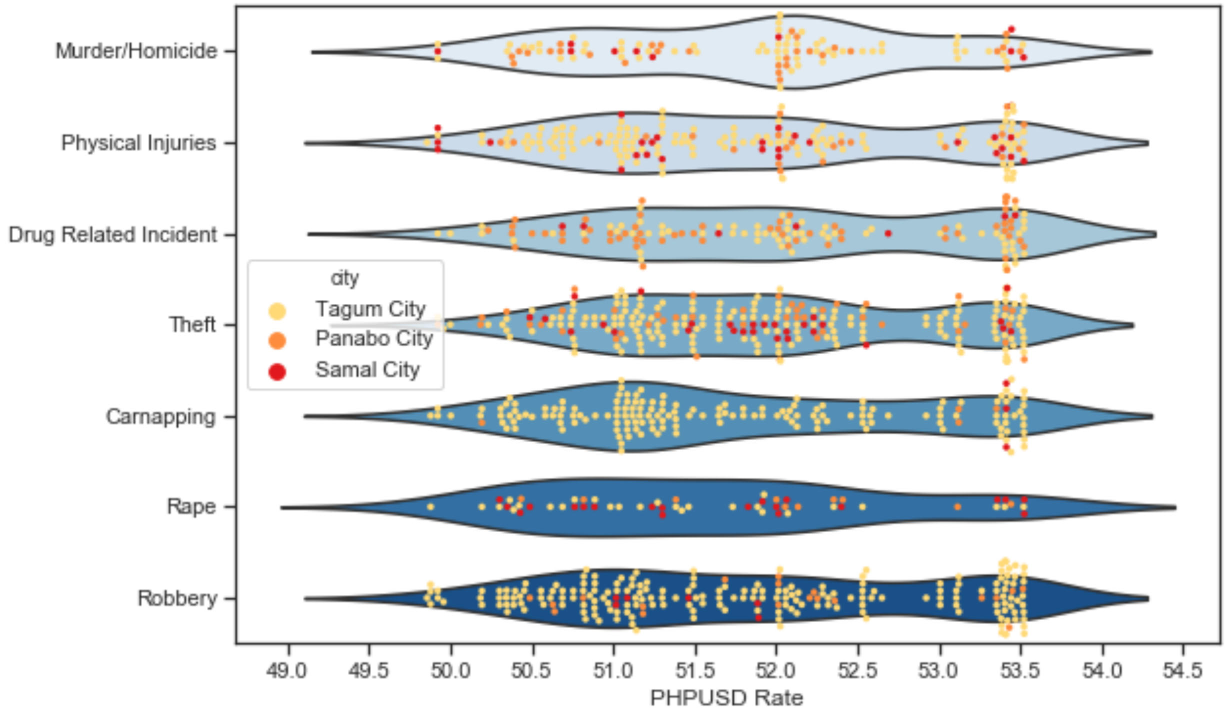


Figure 4.21 Crime Incidence by PHPUSD Rate

Though the rise and fall of currency rates does not necessarily affect crime rate, there are undeniable association shown in the Figure 4.21. It shows that physical injuries, carnapping, and theft mostly happened when PHPUSD rate is between 51.0 and 15.5 or between 53.0 and 53.5. Most murder/homicide crimes happened when PHPUSD rate is 52.0, while drug-related incidents mostly happened when PHPUSD rate us 53.5. Robbery mostly happened if PHPUSD rate is either along 51.0 or 53.5.

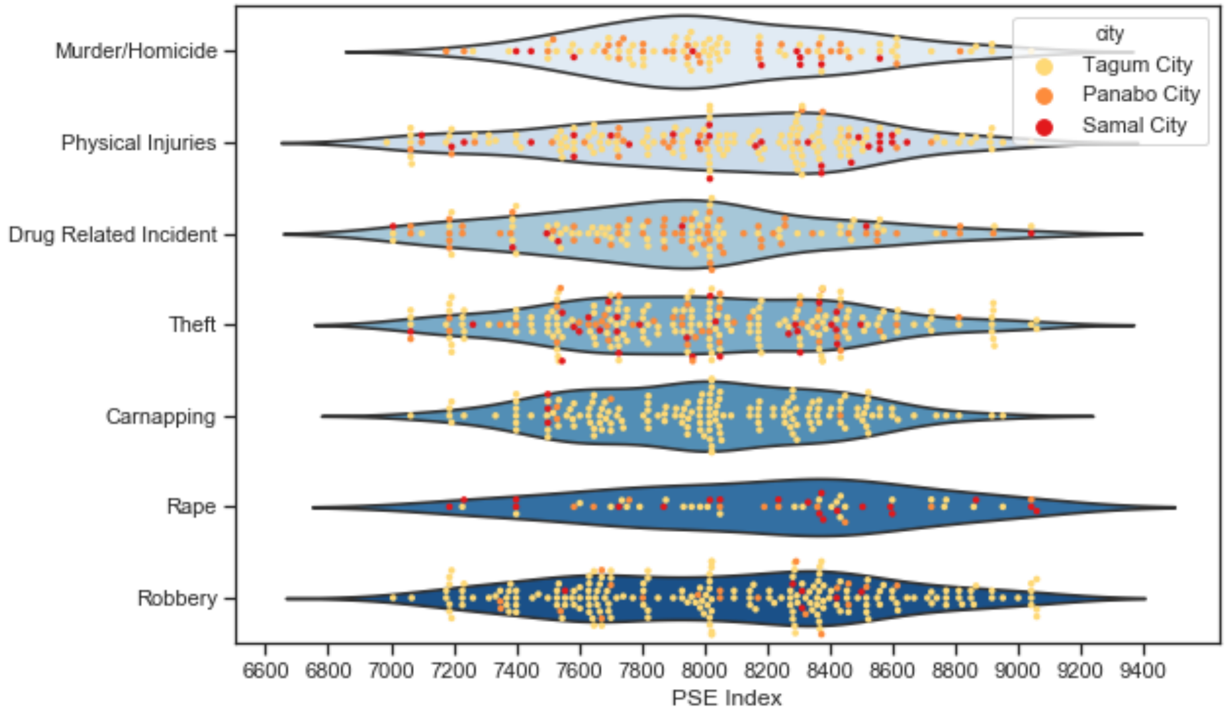


Figure 4.22 Crime Incidence by PSE Index

Figure 4.22 shows that physical injuries, carnapping, theft, and robbery happened mostly when PSE index is 8000. There are also numerous incidences of crimes when PSE index are between 7500 and 7750 and between 8250 and 8500. Other than the ones mentioned, values in the figure do not seem to have any other distinguishable patterns which will isolate a certain type of crime. Though crimes tend to happen throughout the range of PSE index values, this may only mean that prices tend to be very volatile and does not necessarily affect crime.

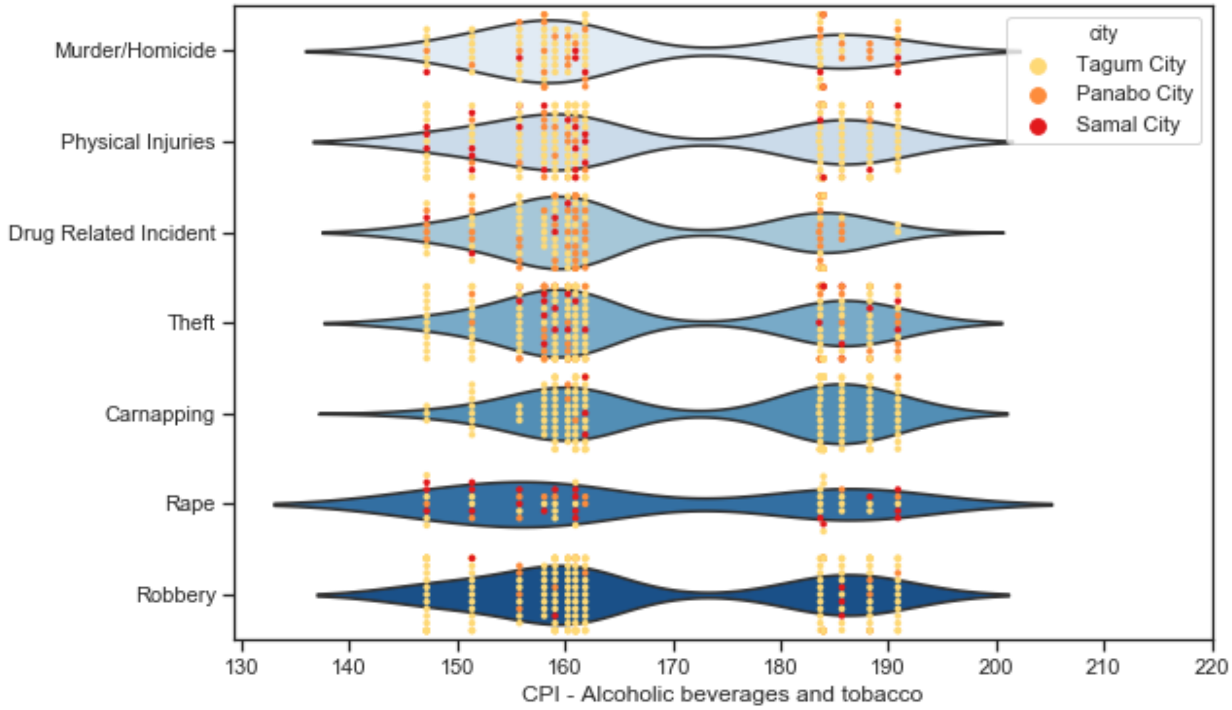


Figure 4.23 Crime Incidence by CPI of Alcoholic Beverages and Tobacco

The consumption of alcoholic drinks and smoking of tobacco may have a huge influence on crime since this variable is consistently important to all three city models. As seen on Figure 4.23, most crimes happen when the Consumer Price Index of alcohol and tobacco are at the low range. Interestingly, crime count drops when CPI of alcoholic drinks and tobacco is at the high range in which people find it expensive.

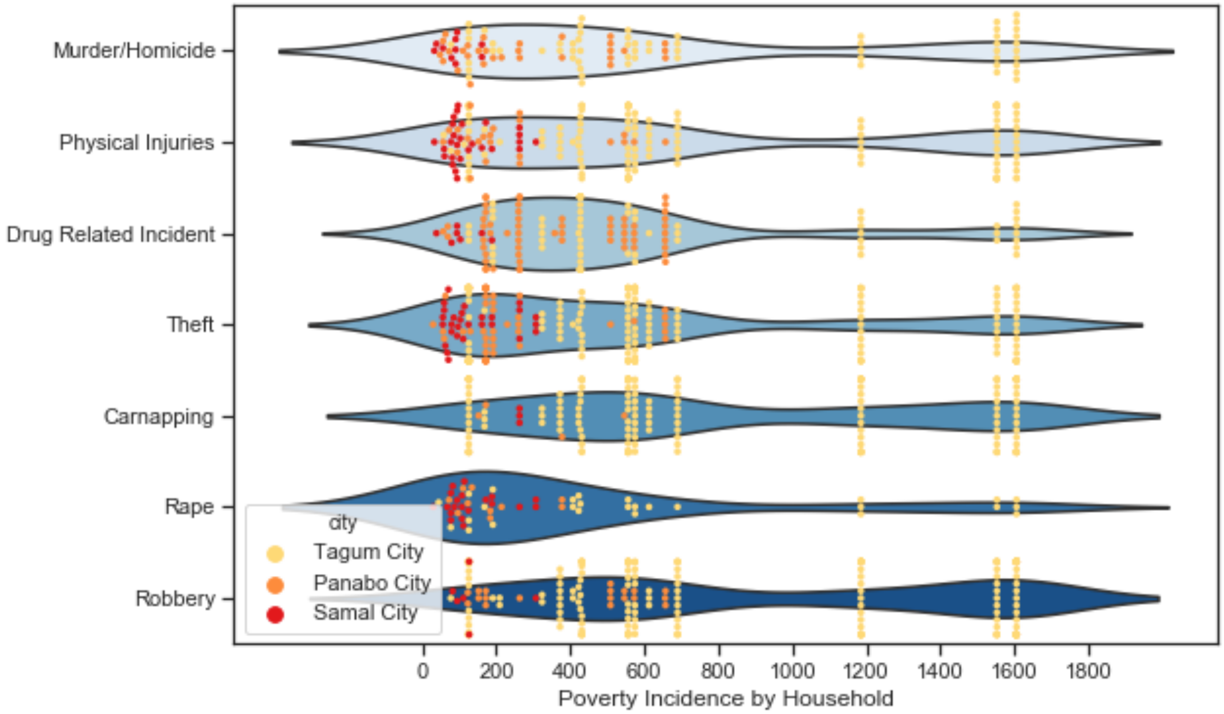


Figure 4.24 Crime Incidence by Household Poverty Incidence

In Figure 4.24, it can be observed that the number of households in the poverty line for Samal City are usually in the lower range from 0 to 350; Panabo City is between 0 up to 700; Tagum City range from 0 up to 1600. Interestingly, the figure shows that an area with low number of families experiencing poverty has more crime incidence than when an area has high number of poor families. This means that an area with a mix of poor and higher income families living together has higher rate of victimization, than in an area where poor families are the norm.

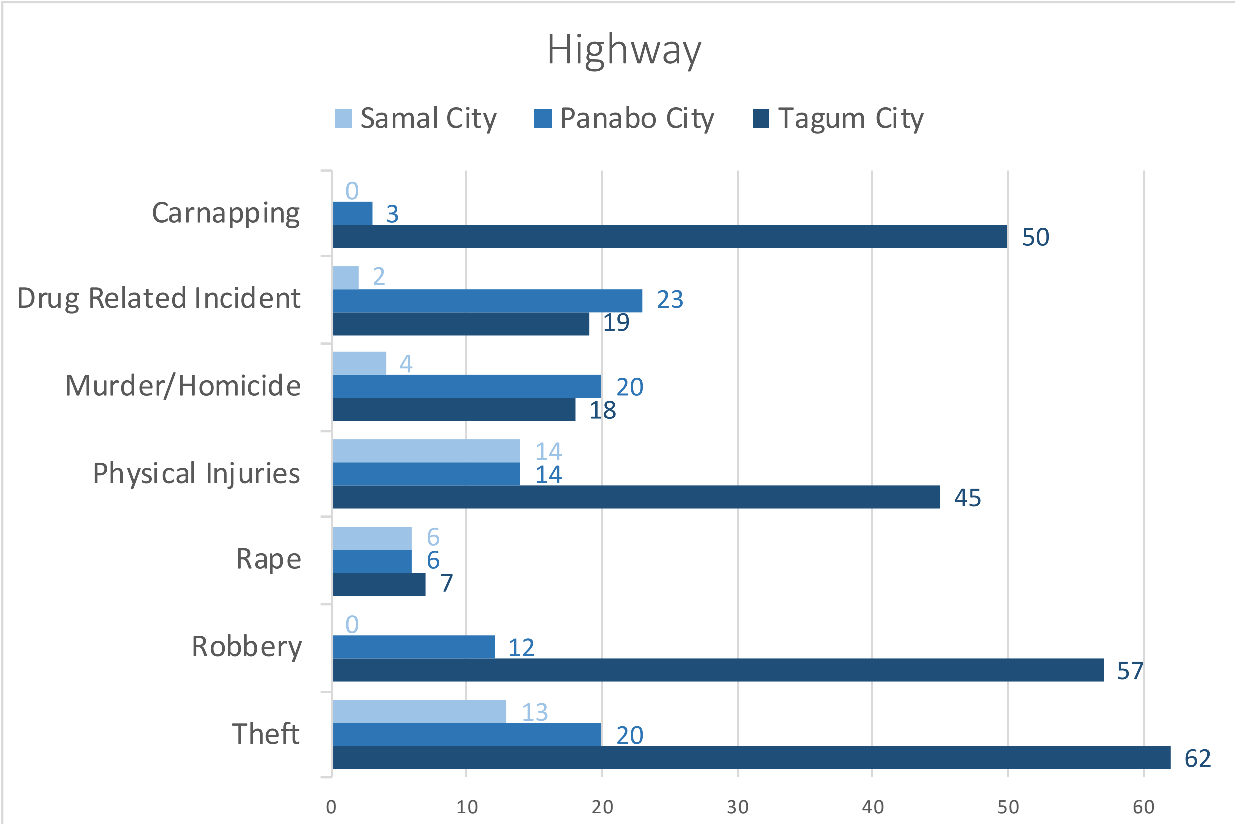


Figure 4.25 Crime Incidence within the Highway Vicinity

The crimes that happen within the vicinity of a highway differ by city as observed on Figure 4.25. In Tagum City, crimes that happen within the vicinity of a highway are theft, robbery, carnapping, and physical injuries. In Panabo City, crimes on the highway usually include drug-related incidents, murder/homicide, theft, physical injuries, and robbery. In Samal City, incidence of physical injuries and theft are frequent on the highway.

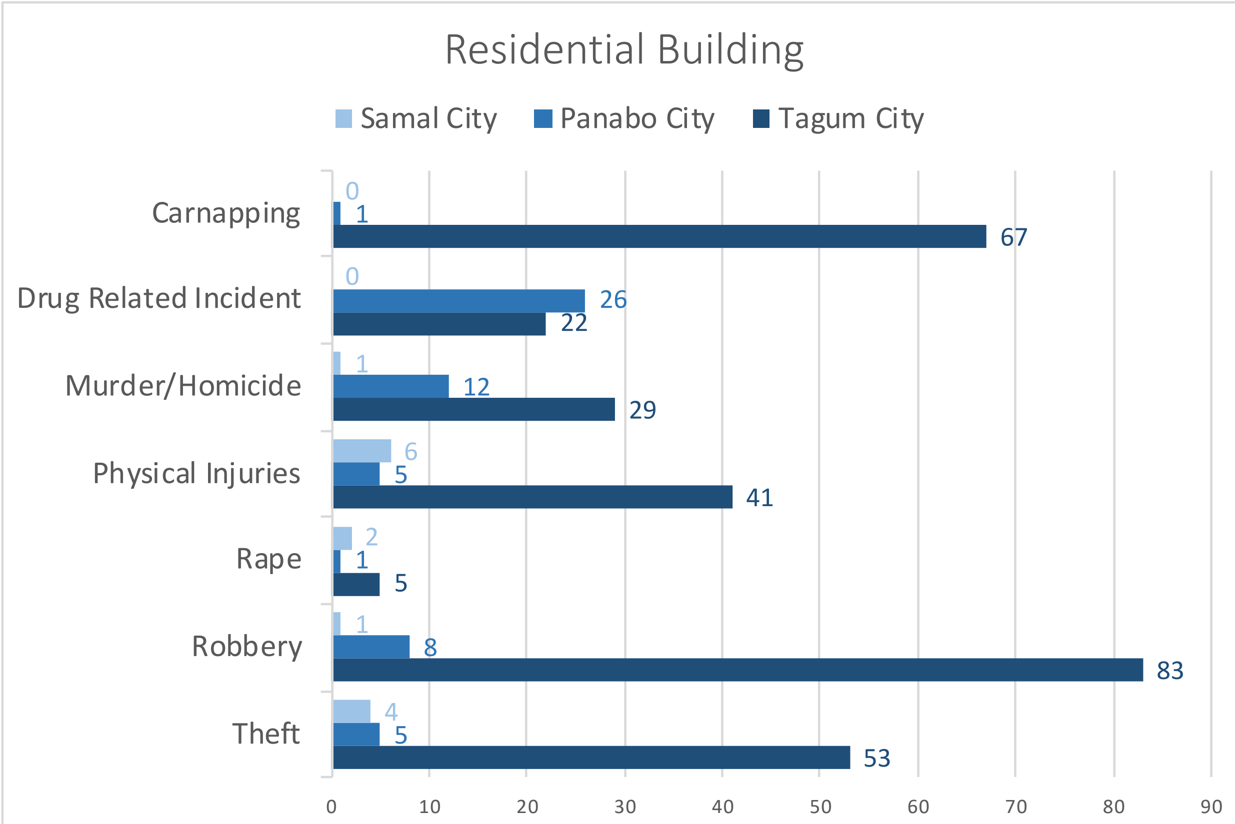


Figure 4.26 Crime Incidence within Residential Building Vicinity

Figure 4.26 shows frequent crime inside or within the vicinity of a residential building. In Tagum City, robbery followed by carnapping and theft are usual crimes on residential areas. Panabo City has high crime count of drug-related incident and murder/homicide; while Samal City has significant count of physical injuries, theft, and rape.

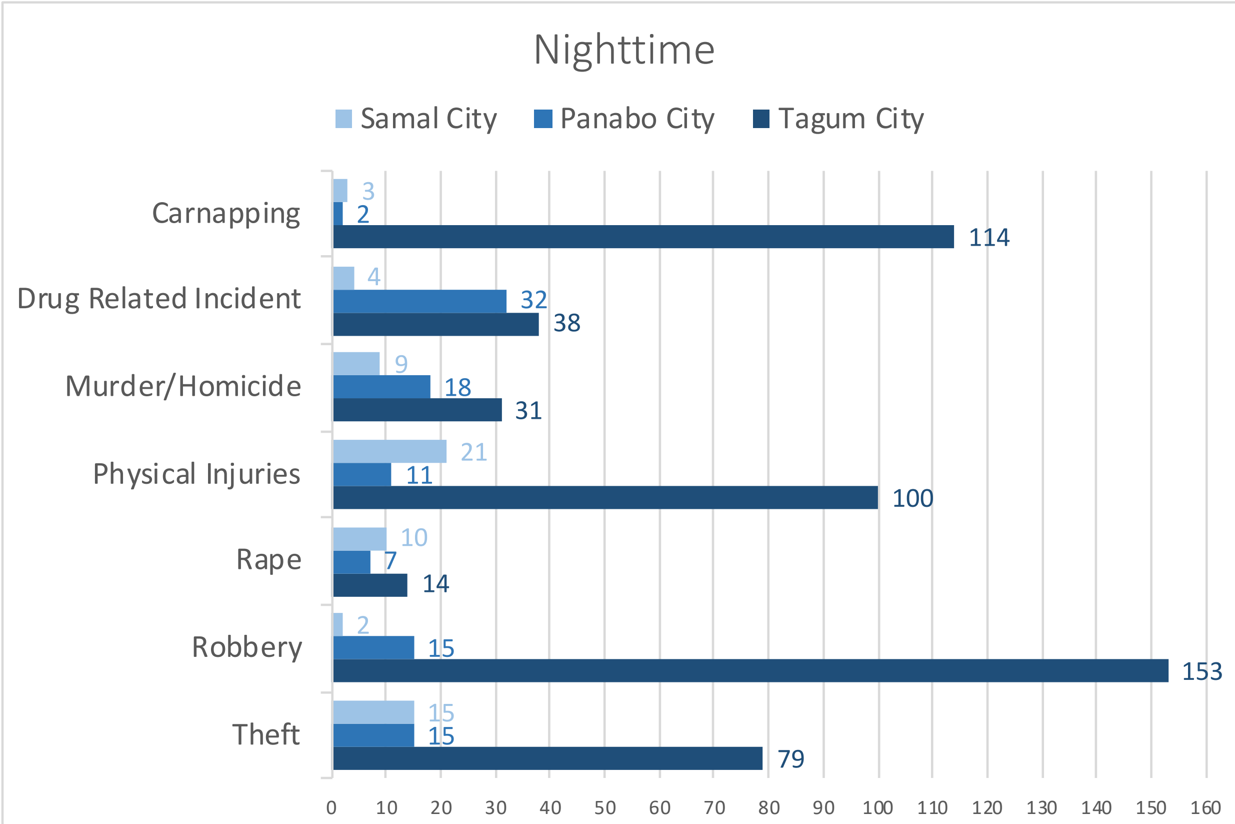


Figure 4.27 Crime Incidence during Night Time

Crimes that happen during the night are shown in Figure 4.27. In Tagum City, robbery, carnapping, physical injuries, and theft usually happens at night. In Panabo City, the common crimes at night are drug-related incidents, murder/homicide, robbery, and theft. In Samal City, most frequent crimes during the dark hours are physical injuries, theft, rape, and murder/homicide.

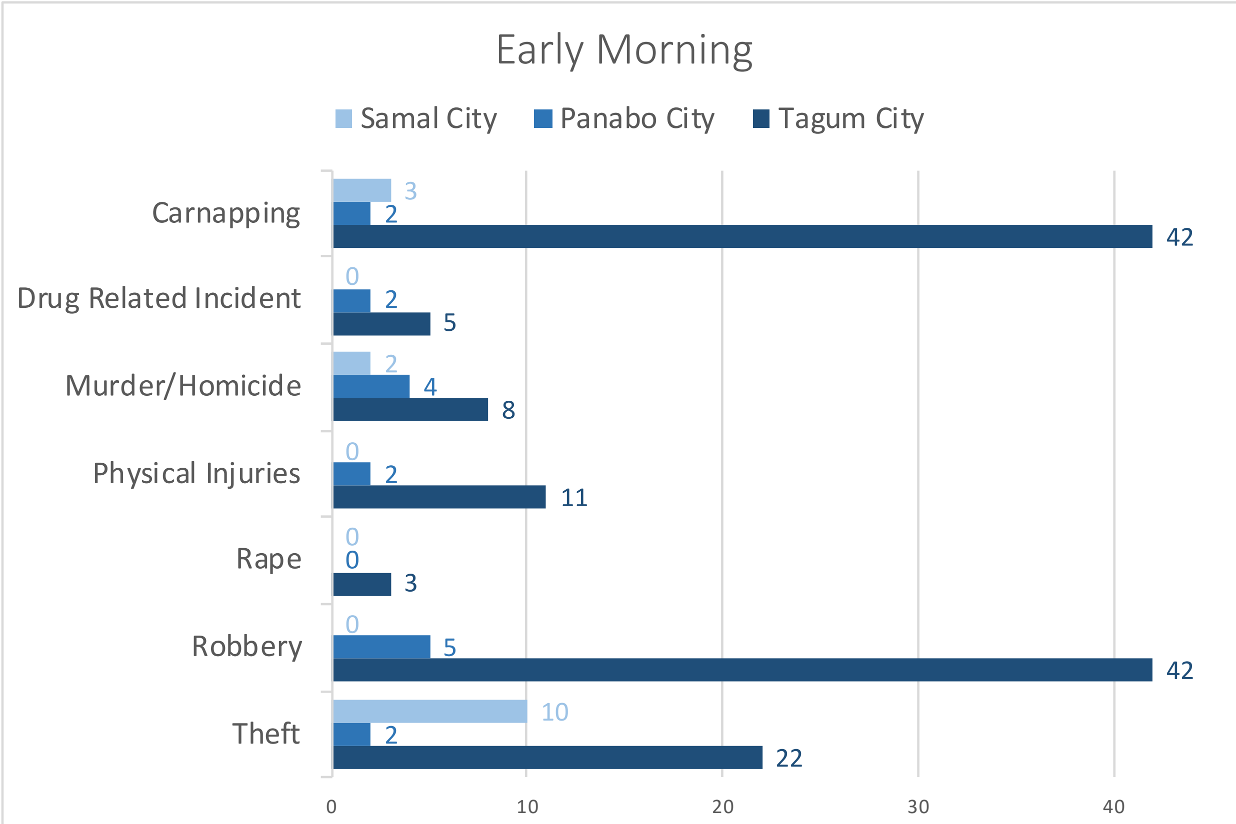


Figure 4.28 Crime Incidence during Early Morning

Figure 4.28 shows crimes that usually happen in the early morning from 4 AM to 8 AM. During these hours, robbery and carnapping are high in Tagum City; Panabo City has numbers of robbery and murder/homicide, while Samal City has crime counts of theft.

4.6 Model Implementation

4.6.1 Model

The three cities have very few in common in terms of how independent variables behave and influence the prediction outputs. To reduce bias in the probability outputs, it is best to utilize separate model for each city in the implementation, rather than use a single model overall.

Three models were used, one each city, for prediction in the model implementation. Parameter settings of Tagum City model is in Code 4.6, Panabo City model in Code 4.7, and Samal City model in Code 4.8. The models were trained using code in Code 4.2. The model outputs were then compiled into a PKL file format using JobLib library as shown in

Code 4.9. The PKL files were loaded on the web server API whenever prediction is requested by the client.

Code 4.6 Tagum City Model

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=40, n_jobs=None,
            oob_score=False, random_state=42, verbose=0, warm_start=False)
```

Code 4.7 Panabo City Model

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=30, n_jobs=None,
            oob_score=False, random_state=42, verbose=0, warm_start=False)
```

Code 4.8 Samal City Model

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
            oob_score=False, random_state=42, verbose=0, warm_start=False)
```

Code 4.9 RFC Model Conversion to PKL File

```
def convert_to_PKL(model, name):
    from sklearn.externals import joblib
    joblib.dump(model, name)
```

4.6.2 Web Server

The web server was an API to access the crime predictive models for prediction. Shown in Code 4.10, the predict API was an HTTP POST function which receives a JSON data format (Code 4.12) from the client. The received data were the values for all required independent variables. These predictor values were then passed to the predictive crime model by *predict_proba()* function to produce probabilities of each crime type. A specific model was used depending on the city as described in section 4.6.1. The API function then returned the probability results in a JSON format (Code 4.11), as a reply to the client.

Code 4.10 Web Server POST Method

```
import logging

from flask import Flask, request
from sklearn.externals import joblib
import pandas as pd
import json

app = Flask(__name__)

@app.route('/api/predict', methods=['POST'])
def predict():
    # get received data
    user_data = request.get_json()
    query_df = pd.DataFrame([user_data])

    # get location data
    social_csv = pd.read_csv('data/social_indicators.csv', encoding='utf-8')
    soci = social_csv[social_csv['location'] == query_df.loc[0,'location']]
    soci = soci.reset_index()
    city = social_csv['city'][0]

    # load model according to city
    if city == 'Tagum City':
        predictmodel =
joblib.load('data/randomforest_dangerpredict_model_tagum.pkl')
    if city == 'Panabo City':
        predictmodel =
```

```
joblib.load('data/randomforest_dangerpredict_model_panabo.pkl')
    if city == 'Samal City':
        predictmodel =
joblib.load('data/randomforest_dangerpredict_model_samal.pkl')

    # get probabilities of each crime type
    prediction = predictmodel.predict_proba(query_df[independent_columns])
    crime_predictions = {}
    x=0
    while x < len(prediction[0]):
        crime_predictions[crime_labels[x]] = prediction[0][x]
        x+=1

    #return JSON format
    return json.dumps(crime_predictions)
```

Code 4.11 Web Server JSON Reply Data

```
{"Carnapping": 0.16,
"Drug Related Incident": 0.48,
"Murder/Homicide": 0.1,
"Physical Injuries": 0.16,
"Rape": 0.06,
"Robbery": 0.0,
"Theft": 0.04}
```

Code 4.12 Mobile Application JSON Sent Data

```
{"day_Tuesday":"0",
"Recreational Area":"1",
"Temp (deg celsius)":"30",
"Consumer Price Index -Alcoholic beverages and tobacco":"158.0",
"bank lending rates":"5.653",
"Commercial Building":"0",
"School":"0",
"Highway":"0",
"Parking Area":"0",
"Weather_Clear":"0",
"Pharmacy":"0",
"Weather_Rainy":"0",
"php-usd-rate":"51.5",
"Pressure (mb)":"1009",
"Community Center":"0",
"Consumer Price Index  - all items":"119.0",
"Highway Tertiary":"0",
"time_epoch_Early Morning":"0",
```

```
"Cemetery":"0",
"time_epoch_Evening":"0",
"Consumer Price Index -transport":"105.0",
"day_Friday":"0",
"time_epoch_After Work-Hours":"0",
"day_Monday":"0",
"Consumer Price Index -Housing, water, electricity, gas, and other fuels":"117.0",
"day_Wednesday":"1",
"day_Sunday":"0",
"Transport Terminal":"0",
"time_epoch_After Midnight":"0",
"day_night_daylight":"0",
"Government Office":"0",
"Hospital":"0",
"Sports Center":"0",
"Tourist Attraction":"0",
"Wind (km\/h)":"10",
"PSE-index-Close":"8300.0",
"Bar":"0",
"Bank":"0",
"Mall":"0",
"Park":"0",
"Road":"1",
"Beach":"0",
"Cloud":"37",
"Hotel":"0",
"inflation rate":"5.0",
"time_epoch_Afternoon":"1",
"Restaurant":"0",
"savings deposit interest rate":"0.765",
"Highway Secondary":"0",
"Humidity":"73",
"Highway Primary":"0",
"Consumer Price Index -Restaurant and miscellaneous goods and services":"123.0",
"Police Station":"0",
"Highway Residential":"0",
"Residential Building":"0",
"Post Office":"0",
"day_Thursday":"0",
"Highway Pedestrian":"0",
"Pawnshop":"0",
"Weather_Cloudy":"1",
"Feels Like (deg celsius)":"30",
"Fire Station":"0",
"Greenfield":"0",
```

```
"Gas Station":"0",
"time_epoch_Morning":"0",
"day_Saturday":"0",
"Precip (mm)":"1.2",
"day_night_nighttime":"1",
"location":"TagumCity_Madaum2",
"Marketplace":"0",
"Bridge":"0",
"Church":"0",
"Clinic":"0",
"Private Office":"0",
"Convenience Store":"0",
"Industrial Building":"0"}
```

4.6.3 Mobile Application Data Request

The main function of the mobile application was the *predictDanger()* function shown in Code 4.13. The *predictDanger()* function executes all needed steps to request crime probability data from the web server. First, the function will check the integrity of all independent variable values. This was to make sure all data were correctly set and has correct JSON format similar to Code 4.12. Then it will start an asynchronous process of sending an HTTP POST request to the web server using the *DangerPredictApi* class (Code 4.13). The application will wait for the server reply and then display the response accordingly.

The code for displaying server response is shown in Code 4.14. The crime probabilities were displayed using the function *onApiPredictEvent()*. This function will open a new activity window to render the results in a bar graph. In case the mobile application was unable to contact the server, an error window will pop up as coded in *onApiErrorEvent()* function.

The whole process of requesting data from mobile application to the web server is summarized in the Figure 4.29.

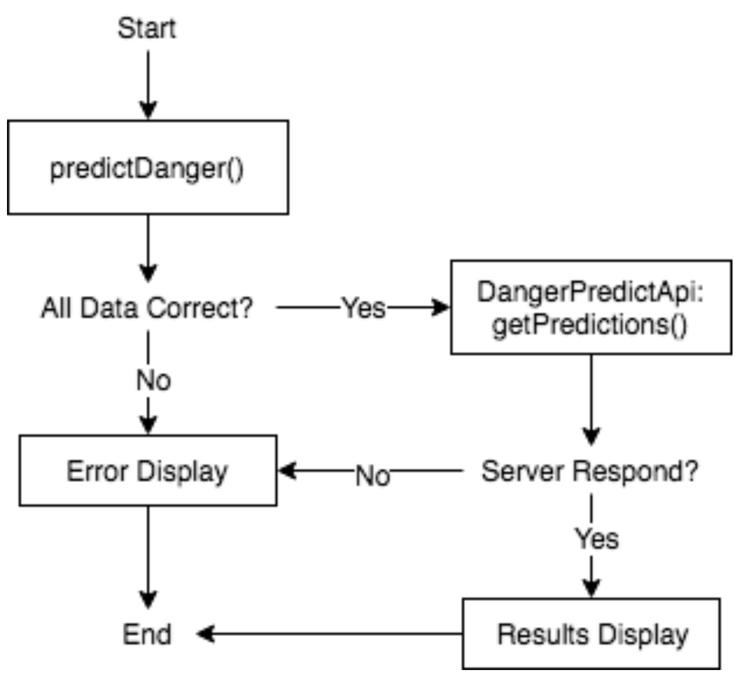


Figure 4.29 Data Request Process Flow

Code 4.13 Mobile Application Predict Danger Function

```
public void predictDanger(View view) {
    spinner.setVisibility(View.VISIBLE);
    pData.buttonPredict.setEnabled(false);
    if(allDataValid()) {
        executePrediction(allData);
    }
}
public void executePrediction(ArrayMap<String,String> data) {
    DangerPredictApi apiPredict = new DangerPredictApi();
    apiPredict.registerApiEventListener(this);
    apiPredict.getPredictions(data);
}
public class DangerPredictApi {
    private static String baseURL = "https://dangerpredict.appspot.com/";
    private ApiEventListener mApiListener;
    public void registerApiEventListener(ApiEventListener mApiListener) {
        this.mApiListener = mApiListener;
    }
    void getPredictions(ArrayMap<String,String> data) {
        RequestQueue requstQueue = Volley.newRequestQueue((Context) mApiListener);
        String url = baseURL.concat("api/predict");
        JsonObjectRequest jsonobj = new JsonObjectRequest(
                Request.Method.POST,
                url,
                new JSONObject(data),
                new Response.Listener<JSONObject>() {
                    @Override
                    public void onResponse(JSONObject response) {
                        mApiListener.onApiPredictEvent(response);
                    }
                },
                new Response.ErrorListener() {
                    @Override
                    public void onErrorResponse(VolleyError error) {
                        mApiListener.onApiErrorEvent(error);
                    }
                }
        );
        requstQueue.add(jsonobj);
    }
}
```

Code 4.14 Mobile Application Display Server Response

```
@Override
public void onApiPredictEvent(JSONObject response) {
    openDialog(response, "predict",null);
}
@Override
public void onApiErrorEvent(VolleyError error) {
    openDialog(null, null, error);
}
private void openDialog(JSONObject resultsJson, String methodHttp, VolleyError
error) {
    String resultStr = new String();
    String titleStr = new String();
    if (error != null) {
        resultStr = error.toString();
        titleStr = "Network Error";
        dialogResults.setContentView(R.layout.activity_prediction_popup);
        TextView textTitle = (TextView) dialogResults.findViewById(R.id.title);
        textTitle.setText(titleStr);
        TextView textResult = (TextView)
dialogResults.findViewById(R.id.results);
        textResult.setText(resultStr);
        Button txtClose = (Button) dialogResults.findViewById(R.id.close);
        txtClose.setOnClickListener(new View.OnClickListener() {
            @Override
            public void onClick(View v) {
                dialogResults.dismiss();
            }
        });
        dialogResults.getWindow().setBackgroundDrawable(new
ColorDrawable(Color.TRANSPARENT));
        dialogResults.show();
        spinner.setVisibility(View.GONE);
        pData.buttonPredict.setEnabled(true);
    }
    else if (methodHttp == "predict") {
        sortJsonObject(resultsJson);
        //find highest percentages
        ArrayList<String> highestCrime = findCrimeLabels(sorted.get(0));
        String advise = new String();
        Double d1 = sorted.get(0)*100;
        Double d2 = new Double("50.0");
        if (d1.compareTo(d2) == 1 || d1.compareTo(d2) == 0) {
            advise = String.format("Travel to the place is\n[NOT
Advisable]\nsince there is 50%% or more chance of \n%s - %.2f%%\nto
happen.\n\n***Complete Assessment***",highestCrime.get(0), d1);
        }
        else if (d1.compareTo(d2) == -1) {
            advise = "Travel to the place is\n[Advisable but with
```

```
Precautions]\nsince not one crime has\nover 50% chance of
happening.\n\n***Complete Assessment***";
        }
        titleStr = "Calculated Risks";
        Intent intent = new Intent(getBaseContext(), PredictionBarGraph.class);
        intent.putExtra("TITLE_STR", titleStr);
        intent.putExtra("ASSESS_STR", advise);
        for (int i = 0; i < 7; i++) {
            String name1 = new String();
            String name2 = new String();
            name1 = String.format("%s_%s","CRIME",String.valueOf(i));
            name2 = String.format("%s_%s","CRIME_VALUE",String.valueOf(i));
            intent.putExtra(name1, pData.crime_labels[i]);
            intent.putExtra(name2, String.valueOf(unsorted.get(i)*100));
        }
        intent.putExtra("CRIME_DATA", unsorted);
        startActivity(intent);
    }
}
private ArrayList<String> findCrimeLabels(Double level) {
    ArrayList<String> crime = new ArrayList<String>();
    for (int i = 0; i < sorted.size(); i++){
        Double current = unsorted.get(i);
        if (current.compareTo(level) == 0) {
            crime.add(pData.crime_labels[i]);
        }
    }
    return crime;
}
private void sortJsonObject (JSONObject json) {
    String temp = new String();
    unsorted = new ArrayList<Double>();
    sorted = new ArrayList<Double>();
    try {
        for (int i = 0; i < json.length(); i++) {
            temp = json.get(pData.crime_labels[i]).toString();
            unsorted.add(Double.parseDouble(temp));
            sorted.add(Double.parseDouble(temp));
        }
        Collections.sort(sorted, Collections.reverseOrder());
    }
    catch (JSONException e) {
    }
}
```

4.6.4 Mobile Application User-Interface

The mobile application served as a user interface to get predictor values to predict probabilities of each crime label. Every independent variable was represented in the user interface of the mobile application. The user must indicate values of each feature before it can send a request in a JSON format to the web server.

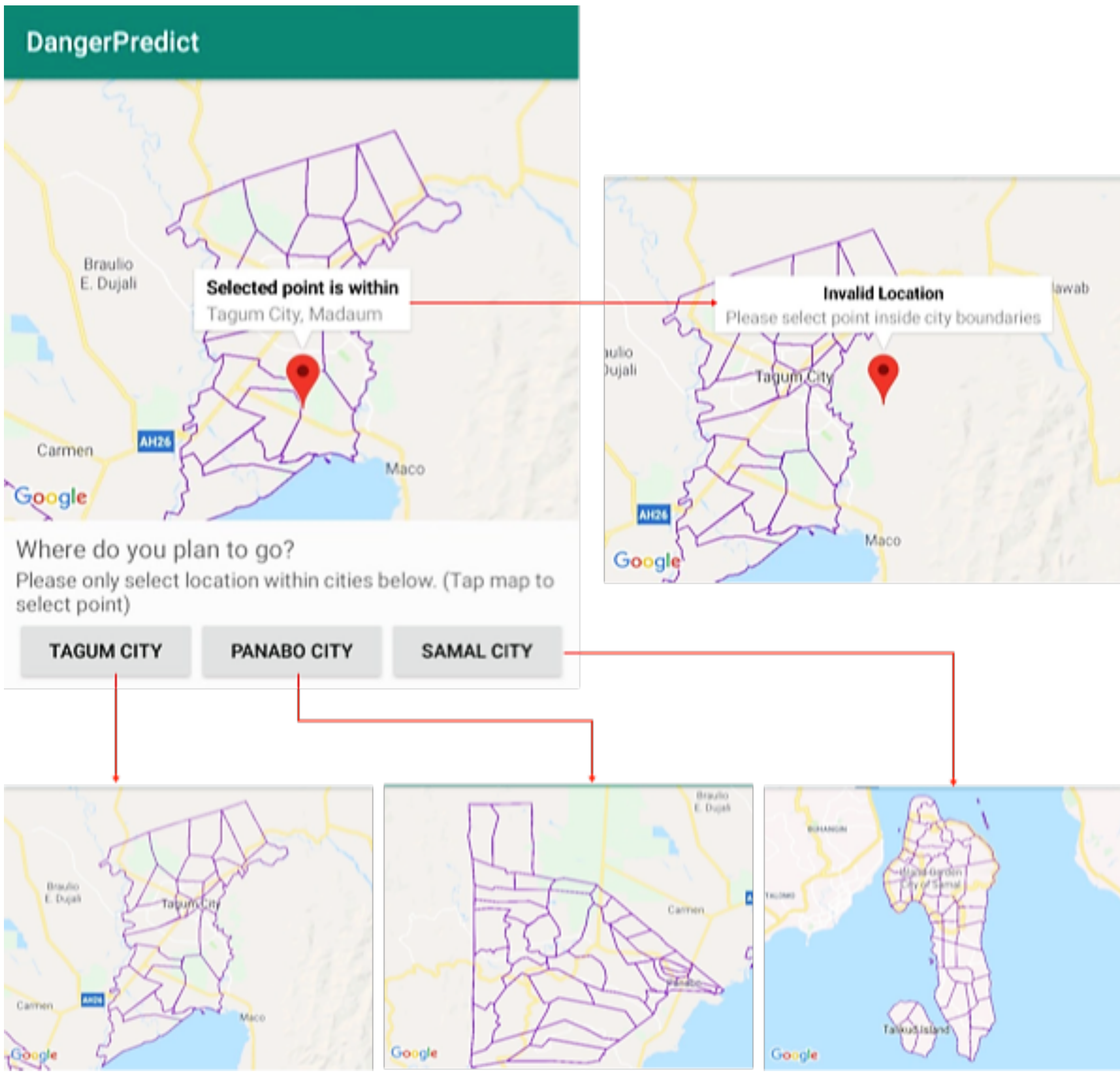


Figure 4.30 Mobile UI - Social Data

♦ ***Social Data Section***. Social data can be set using the map shown in Figure 4.30. The user must select a location within the drawn boundaries. Each boundary represents one barangay which has the complete values for all social variables. The complete list of social independent variable values for each barangay is in Appendix B. Failure to set a valid location will warn the user to select a location within the boundary, or else, prediction will not proceed.

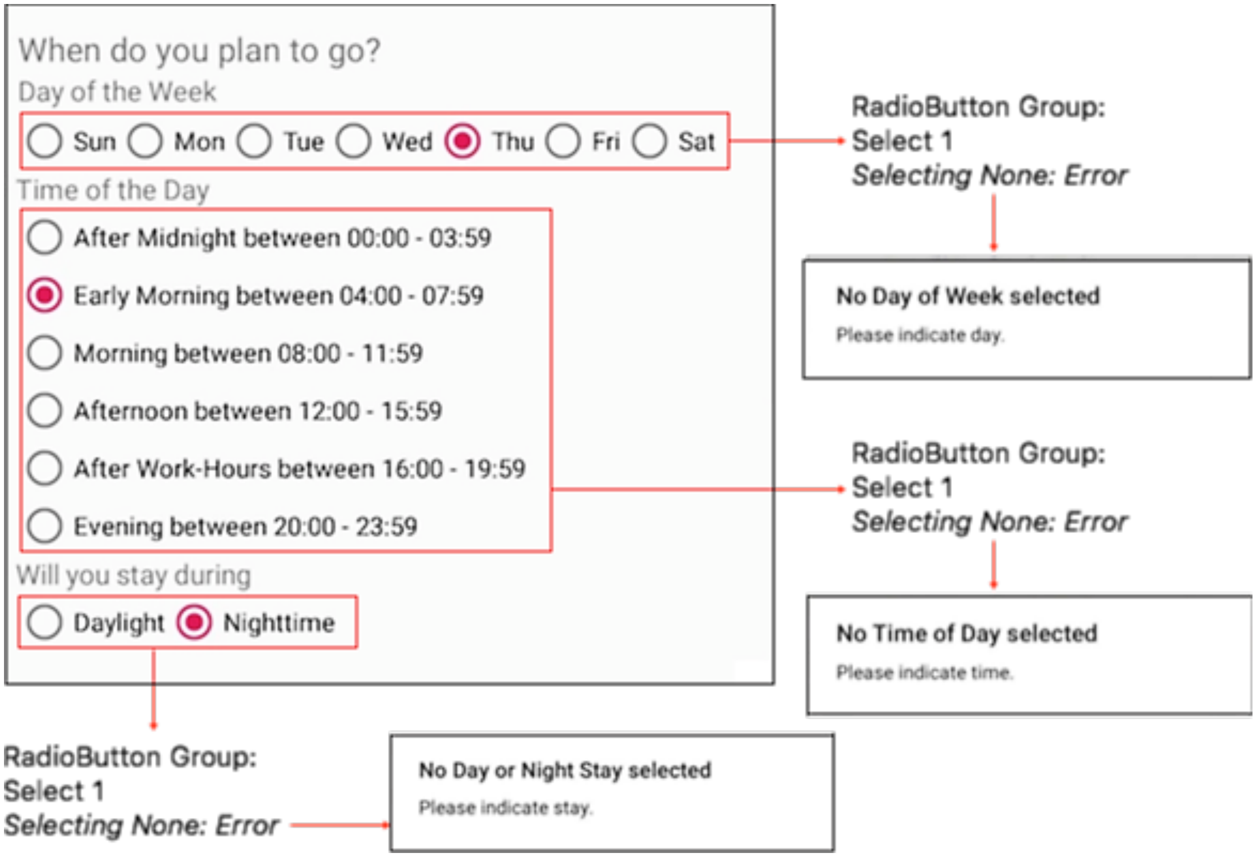


Figure 4.31 Mobile UI - Day/Time Data

♦ ***Time/Day Data Section***. To set day, time, and stay to the indicated location, user will have to set values in the interface shown in Figure 4.31. Failure to set values for any of the variables will show an error message.

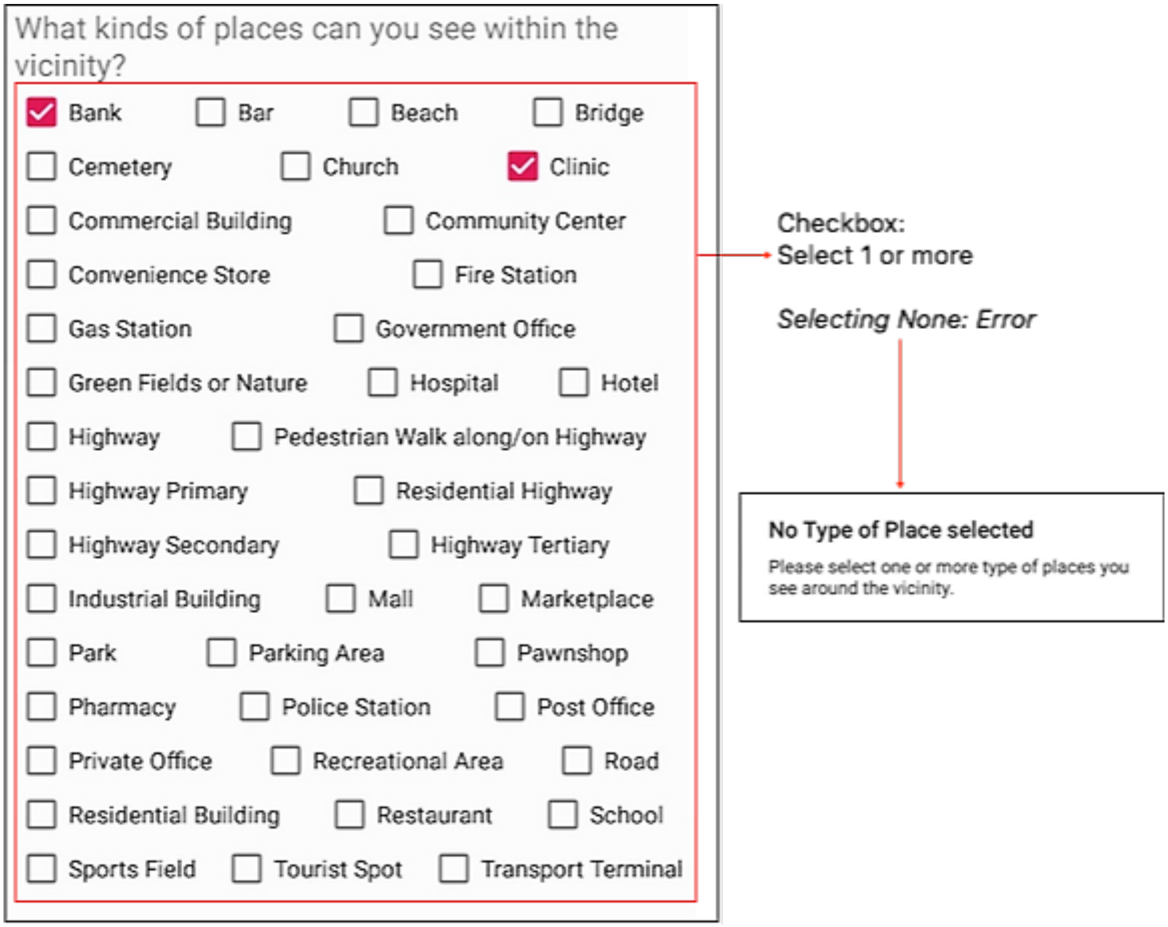


Figure 4.32 Mobile UI - Places Data

♦ ***Places Data Section***. To set which types of places are within the vicinity of the location, user must toggle at least one place present using the interface in Figure 4.32. Failure to select at least one place will show an error message.

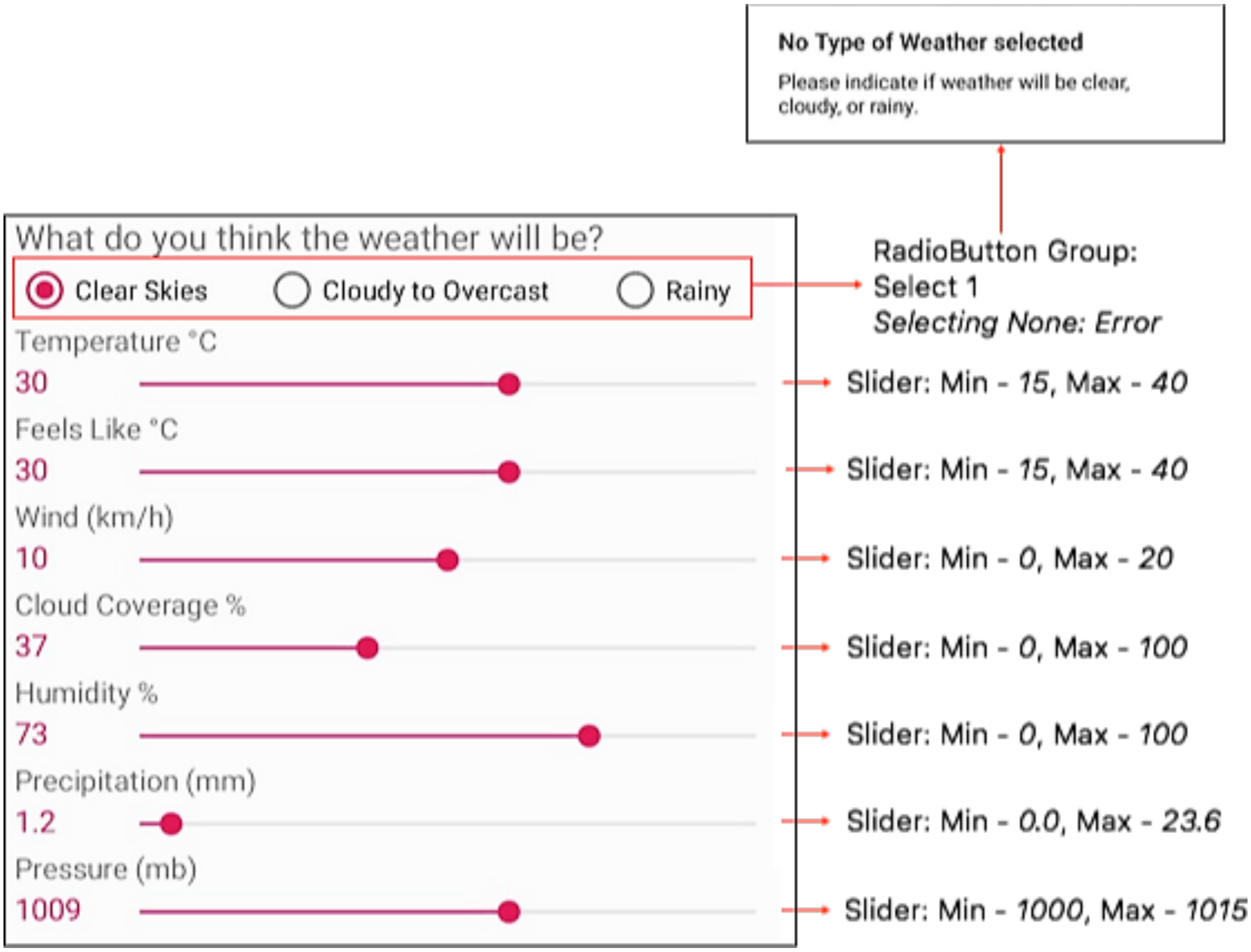


Figure 4.33 Mobile UI - Weather Data

♦ ***Weather Data Section***. Weather data can be set using interface in Figure 4.33. Failure to select one weather condition will show an error message. The minimum and maximum values of the sliders were based on the minimum and maximum values present in the data for each corresponding independent variable.

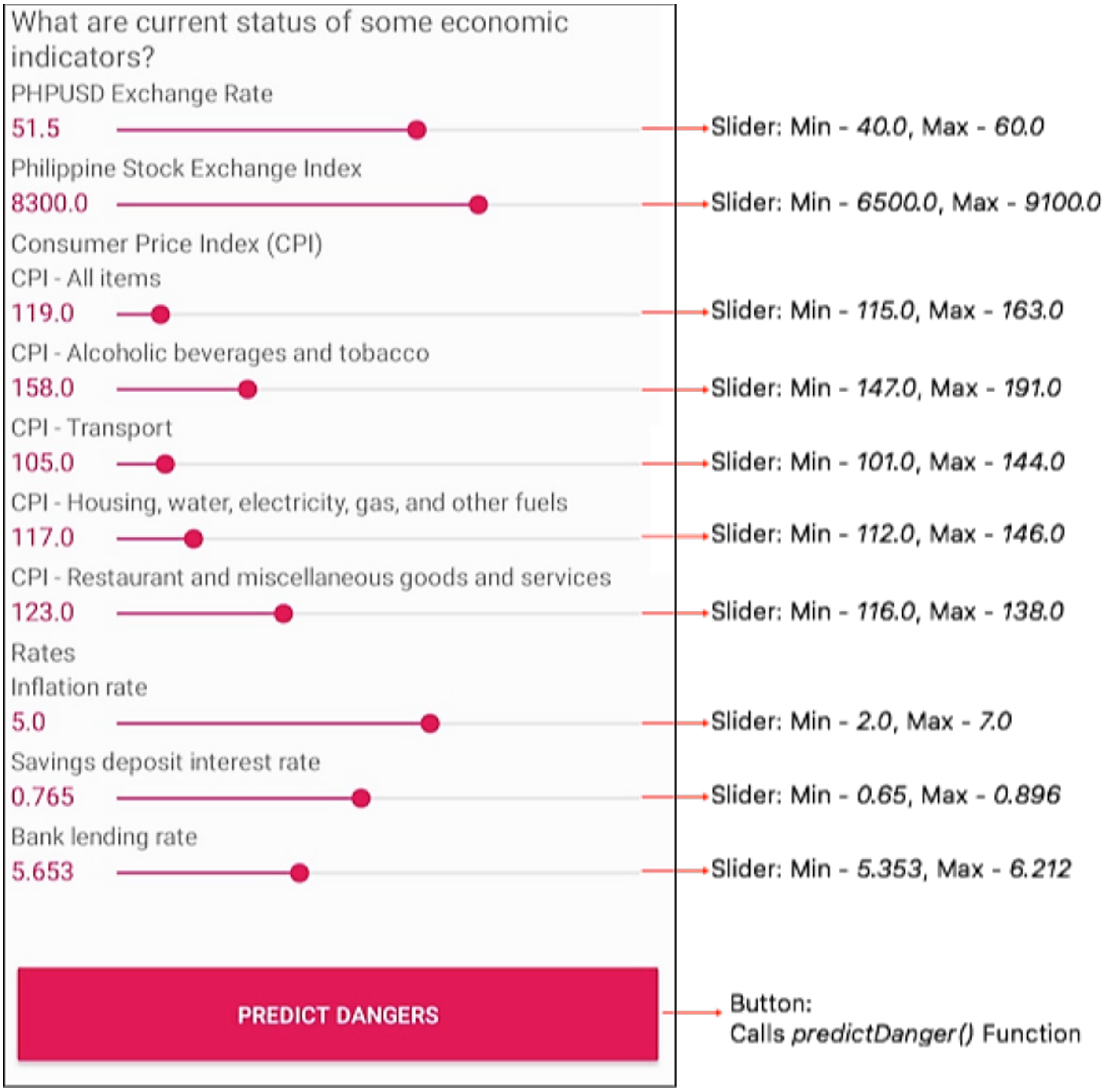


Figure 4.34 Mobile UI - Economic Data

- ***Economic Data Section***. Economic data can be set using interface in Figure 4.34. The minimum and maximum values of the sliders were based on the minimum and maximum values present in the data for each corresponding independent variable.
- ***Predict Button***. After all required data are set; the user will be able to get probabilities by tapping on the *Predict Dangers* button shown in Figure 4.34. This button will call the main function *predictDanger()* as coded in Code 4.13.

♦ ***Results Window***. When the mobile application receives the reply from the web server, it will display crime probabilities as a bar graph similar to the ones shown in Figure 4.35 and Figure 4.36. The application will advise the user not to travel to the indicated area on the map if one crime type has 50% or more chance of happening; otherwise, the application will advise the user to proceed with precautions.

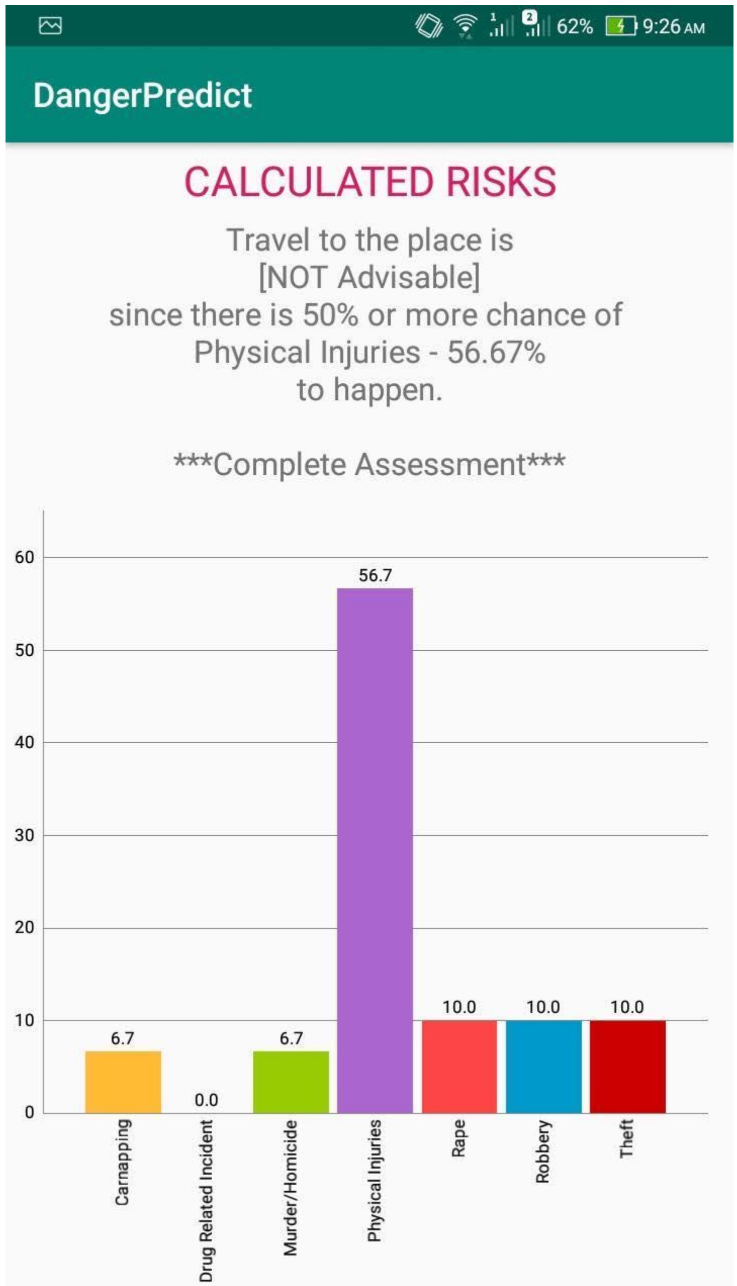


Figure 4.35 Mobile UI - Sample Probability Results 1

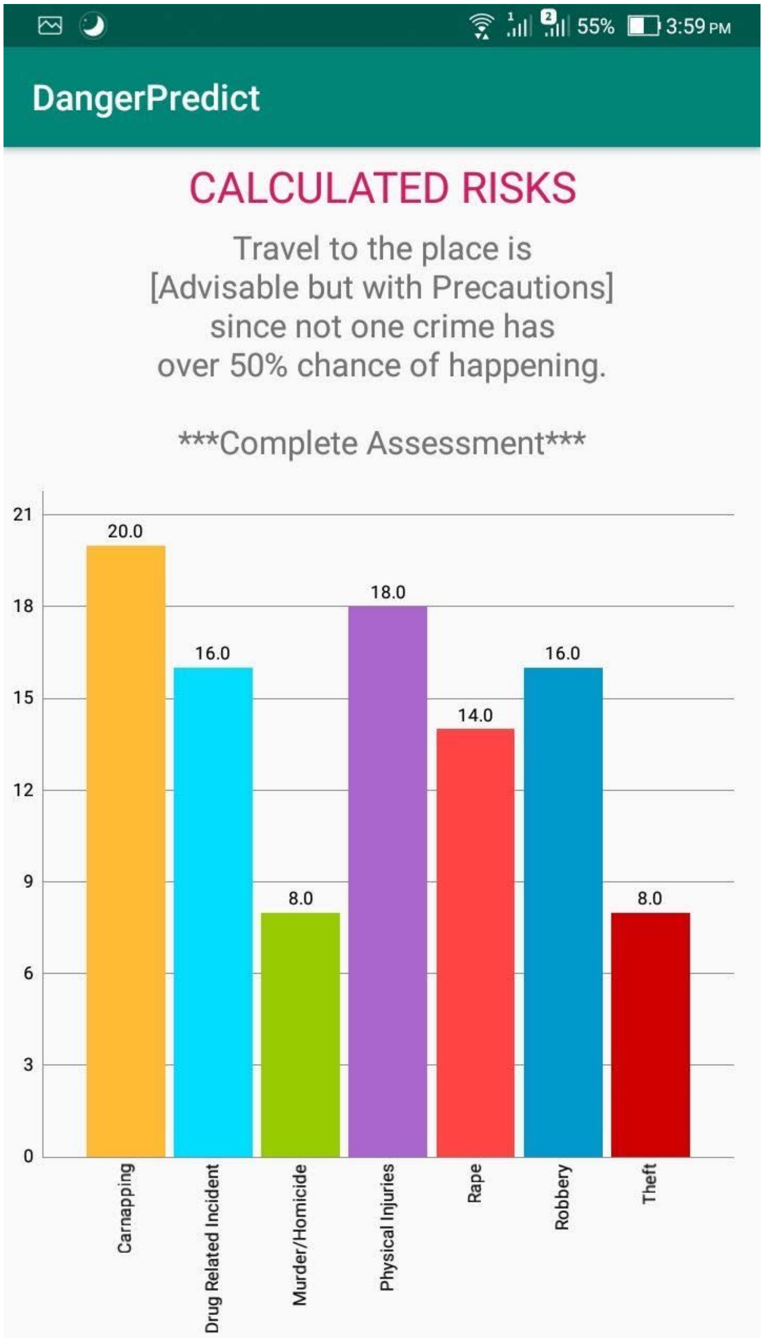


Figure 4.36 Mobile UI - Sample Probability Results 2

Chapter 5. Conclusion

This study aimed to measure the risk of a place when it comes to different types of crimes - *Murder/Homicide, Physical Injuries, Drug Related Incident, Theft, Carnapping, Rape, and Robbery*. The applied solution was to develop a machine learning model for a mobile application where crime risk predictions will be calculated and displayed. This study had four objectives to accomplish. First was to identify significant crime predictors; second objective was to use these predictors to build a crime predictive model; third objective was to measure the performance of the model and then, lastly, the fourth objective was to deploy the most appropriate predictive model as backend for the crime risk assessment mobile application. All objectives were achieved with findings described in summary.

There were five types of factors found to influence crime. These crime factors were time/day, type of place, social indicators, economic indicators, and weather. The mentioned crime factors were used as independent variables for the crime predictive model. The training and testing data had 114 features to predict one dependent variable with seven unique values of crime. The Random Forest Classifier, available in the Scikit Learn machine learning Python library, was used to train the predictive model. Three models were created, one each for the cities of Tagum, Panabo, and Samal.

Through model evaluation, it was found out that the best performance scores of the all models were not desirable. All models were generally poor in generalization and accurately pinpointing one crime class. Though this was the case, the purpose of the models to provide probabilities of each crime type was still achieved. Every predictor contributed to the calculated crime risk probabilities. The most important features to the Random Forest Classifier turned out to be mostly weather and economic variables. These features were consistently on the top most important predictors among all three models.

The Random Forest Classifier model with best performance scores for each city was selected. These models were then compiled into a PKL file and deployed on the web server. The mobile interface has enabled the user to set values of each crime predictors. After all predictor values were correctly set, the mobile application sent the values to the web server, through an HTTP POST call method, for risk calculations. The web server replied with crime probabilities of each crime type, and then, displayed by a bar graph on the results window. The mobile application will advise the user not to travel to the area if one crime has 50% or more risk percentage; otherwise, the user will be advised to proceed with precautions.

5.1 Recommendations

There are still many areas for discovery in this line of study. However, the leading three recommendations identified which will further improve this kind of project are the following:

- The mobile application with predictive crime risk assessment model has the capability to predict crime; however, it cannot predict the absence of all types of crime. Since the model returns probabilities of crime, there will be instances when one type of crime has zero chance of happening, yet it also translates that another type of crime will have a greater risk probability. It is therefore recommended to develop a system that can recognize crime-free instances since it is undeniable that crime does not happen all the time.
- It is recommended to increase quantity of historical crime data for predictive model training. Since the total number of crime data instances used in this study was only 1,094, it had produced an unbalanced dataset for seven crime categories. This means that each crime type was not be properly represented. The scarcity of data was also the cause of undesirable performance scores of the generated models. Increasing the number of crime data may increase model performance in terms of accuracy, precision, recall, and F1 scores. This can be done by including crime data of other localities in the Philippines.
- It will also be interesting to build separate predictive models for each predictor type such as time/day model, weather model, social model, economic model, and places model for crime. Since the models used in the mobile application were trained for all 114 predictors, the user was required to provide values for all types of input features. This task can be daunting at times since it requires the user to execute numerous actions on the mobile application. If there were separate models for each type of predictor, the user may have the option to predict crime based on just one type of crime predictor.

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Appendix A. Philippine Statistics Authority Document Excerpts

This section shows snapshots of all statistical references essential to build social and economic independent variables. PSE index daily historical data was taken from Yahoo Finance (*https://finance.yahoo.com/quote/PSEI.PS/history/*).

TABLE 17.3 Crime Rate by Region[1]
2009 to 2014
(per 100,000 population)

Region	2009	2010	2011	2012	2013	2014
Philippines	552.3	350.0	262.2	227.4	861.7	715.5
National Capital Region (NCR)	510.3	338.9	399.9	464.3	1,237.4	1,178.7
Cordillera Administrative Region	792.5	954.8	464.0	647.8	1,337.5	1,191.2
I Ilocos Region	362.1	340.2	212.8	255.4	862.9	714.6
II Cagayan Valley	595.7	266.1	136.5	112.4	435.6	438.6
III Central Luzon	565.5	532.9	347.1	213.1	617.2	530.6
IVA CALABARZON	386.0	226.0	179.6	149.3	292.1	314.3
IVB MIMAROPA	525.9	240.1	125.2	88.8	654.9	335.4
V Bicol Region	373.6	306.9	213.4	180.8	975.2	822.7
VI Western Visayas	782.9	272.5	127.4	106.6	1,322.5	992.0
VII Central Visayas	533.0	500.1	357.6	290.8	1,119.1	826.7
VIII Eastern Visayas	704.4	134.5	181.6	105.0	476.6	558.0
IX Zamboanga Peninsula	630.2	511.5	234.1	235.5	925.5	885.9
X Northern Mindanao	1,069.1	407.3	357.4	274.3	1,617.9	1,016.9
XI Davao Region	691.3	446.9	345.9	291.5	1,265.2	816.2
XII SOCCSKSARGEN	536.8	269.1	227.5	171.1	933.0	700.1
XIII Caraga	511.4	262.1	208.6	155.0	528.9	648.6
Autonomous Region in Muslim Mindanao	53.9	37.0	28.2	24.9	178.8	124.7

[1] Crime incidents committed per 100,000 population

Notes:

1. Since 2009, the Philippine National Police (PNP) has adopted the National Crime Reporting System (NCRS) that is now being implemented in all PNP units to report crime incidents to the National Headquarters for centralized recording. The old method of crime reporting from the field called Police Regional Office Periodic Report (PROPER) was revised to come up with the Unit Crime Periodic Report (UCPER). To effectively implement the new crime reporting system, all PNP units were required to submit the duly accomplished UCPER to the National Headquarters for consolidation into the NCRS. All crime incidents, whether reported by the victim(s), witness(es) or third party (ies), must be recorded in the Police Blotter (the main source of crime data which shall be the basis for preparing and accomplishing the UCPER). Significant changes in crime reporting were noted with the inclusion of specific violations of special laws such as carnapping and cattle rustling; and addition of crime cleared data that enumerates the number of crime incidents filed in court; that is, crime solution rate will be quantified only if the court issued a decision. Under the current system of crime measurement and analysis, data for 2009 was set as the baseline for future research, study and comparison. Thus, crime statistics in 2009 cannot be compared with those data obtained in the previous years (2008 and earlier) since the parameters were no longer the same;
2. For the period 2009-2012, as per methodology advised by the NSO, the NSCB Technical Staff computed the annual population estimates using curvilinear interpolation at decelerating rates, with the results of the 2000 and 2010 Census of Population and Housing (CPH) as start and end dates of the reference population projections;
3. For the period 2013-2014, the population data used is 2010 Census-based population projections.

Sources: Philippine National Police and Philippine Statistics Authority

TABLE 17.2 Reported Index Crimes by Region and by Type of Crime[1]
2013 - 2016

Region	Against Persons					Against Property				
	Murder	Homicide	Physical Injuries	Rape	Total	Robbery	Theft	Carnapping	Cattle Rustling	Total
2013										
Philippines	9,153	7,007	157,727	8,873	182,760	49,247	124,168	12,341	1,731	187,487
National Capital Region	710	477	10,603	1,325	13,115	13,536	20,046	3,209	-	36,791
Cordillera Administrative Region	98	135	4,819	242	5,294	1,279	5,035	310	21	6,645
1 Ilocos Region	350	491	11,982	494	13,317	1,296	5,043	495	248	7,082
2 Cagayan Valley	258	455	4,288	341	5,342	700	1,314	314	32	2,360
3 Central Luzon	578	801	14,934	883	17,196	3,457	7,766	1,415	50	12,688
4a CALABARZON	1,302	814	7,838	957	10,911	2,490	3,900	1,211	27	7,628
4b MIMAROPA	238	203	5,018	334	5,793	896	1,965	217	35	3,113
5 Bicol Region	454	361	11,997	709	13,521	2,086	7,521	397	134	10,138
6 Western Visayas	572	709	21,409	832	23,522	3,650	15,874	491	194	20,209
7 Central Visayas	745	602	15,245	486	17,078	5,613	13,670	940	102	20,325
8 Eastern Visayas	489	217	5,286	220	6,212	858	3,734	71	25	4,688
9 Zamboanga Peninsula	647	286	7,420	333	8,686	1,565	4,778	608	118	7,069
10 Northern Mindanao	710	596	11,258	415	12,979	4,237	14,566	1,075	361	20,239
11 Davao Region	532	261	10,788	567	12,148	3,346	9,755	318	46	13,465
12 SOCCSKSARGEN	611	307	10,871	371	12,160	2,898	6,407	779	237	10,321
13 Caraga	381	191	2,396	241	3,209	904	2,082	173	19	3,178
Autonomous Region in Muslim Mindanao	478	101	1,575	123	2,277	436	712	318	82	1,548
2014										
Philippines	9,756	3,349	65,743	9,907	88,755	43,726	112,857	13,284	1,368	171,235
National Capital Region	855	655	10,352	1,107	12,969	12,034	22,083	3,286	-	37,403
Cordillera Administrative Region	112	76	2,796	232	3,216	1,196	4,292	208	28	5,724
1 Ilocos Region	327	177	4,105	449	5,058	840	4,515	429	143	5,927
2 Cagayan Valley	257	153	1,766	289	2,465	542	1,160	353	51	2,106
3 Central Luzon	803	242	4,815	1,061	6,921	3,870	7,440	1,861	77	13,248
4a CALABARZON	1,415	241	3,543	1,390	6,589	2,778	4,493	1,824	21	9,116
4b MIMAROPA	207	107	1,252	380	1,946	622	1,166	189	17	1,994
5 Bicol Region	481	162	5,085	938	6,666	2,015	6,525	394	105	9,039
6 Western Visayas	544	290	6,696	849	8,379	2,997	12,636	592	144	16,369
7 Central Visayas	797	206	3,755	631	5,389	4,791	13,017	1,085	117	19,010
8 Eastern Visayas	456	210	4,188	321	5,175	838	4,170	184	31	5,223
9 Zamboanga Peninsula	544	131	3,588	442	4,705	1,536	5,097	525	83	7,241
10 Northern Mindanao	673	238	4,221	432	5,564	3,356	10,148	950	241	14,695
11 Davao Region	651	192	4,355	612	5,810	2,662	6,939	251	48	9,900
12 SOCCSKSARGEN	655	107	3,319	445	4,526	2,212	5,829	699	166	8,906
13 Caraga	435	116	1,339	294	2,184	1,159	2,977	293	25	4,454
Autonomous Region in Muslim Mindanao	544	46	568	35	1,193	278	370	161	71	880
2015	9,643	2,835	49,845	10,298	72,621	31,741	82,751	12,900	997	128,389
2016	11,385	2,337	35,796	9,324	58,842	21,217	49,613	9,323	464	80,617

[1] Refer to crimes that are serious in nature and occur with sufficient frequency and regularity for them to serve as index in crime analysis.
Source: Philippine National Police

- City of Tagum has 23 barangays. Barangay Visayan Village had the biggest population in 2015, followed by Barangay Mankilam with 38,963, and the Barangay San Miguel with 17,317 persons. The combined population of these three barangays accounted for about 37.22% percent of the population in City of Tagum in 2015. *See Table 3*.

- Barangay San Agustin was the smallest barangay in 2015, in terms of population size, with 1,115 persons. *See Table 3*.

Table 3. Population of City of Tagum
(Based on the 2000, 2010, and 2015 Censuses)

Barangay	Total Population		
	2000	2010	2015
Apokon	16,171	26,876	29,743
Bincungan	3,418	3,880	4,227
Busaon	2,984	2,672	2,847
Canocotan	3,956	6,215	8,136
Cuambogan	3,122	8,471	10,612
La Filipina	6,206	12,099	15,390
Liboganon	2,097	2,103	2,279
Madaum	8,552	9,838	10,721
Magdum	6,815	10,588	10,216
Mankilam	20,107	38,729	38,963
New Balamban	1,382	1,625	1,464
Nueva Fuerza	913	1,564	1,952
Pagsabangan	3,843	4,822	5,250
Pandapan	1,223	2,242	2,386
Magugpo Poblacion	8,532	4,820	3,165
San Agustin	609	1,206	1,115
San Isidro	4,140	4,704	4,796
San Miguel (Camp 4)	8,460	16,430	17,317
Visayan Village	28,932	35,323	40,297
Magugpo East	15,482	15,971	14,427
Magugpo North	9,486	8,695	9,344
Magugpo South	11,475	10,548	10,832
Magugpo West	11,626	13,380	13,965

Source: Philippine Statistics Authority, *2000 and 2010 Census of Population and Housing and 2015 Census of Population*

Table 3. Population of Panabo City
(Based on the 2000, 2010, and 2015 Censuses)

Barangay	Total Population		
	2000	2010	2015
A. O. Floirendo	6,082	5,913	4,848
Datu Abdul Dadia	3,592	5,264	5,793
Buenavista	757	592	800
Cacao	984	1,071	1,196
Cagangohan	11,028	15,406	13,776
Consolacion	1,012	2,435	1,747
Dapco	3,971	4,046	4,068
Gredu (Pob.)	8,938	11,113	16,543
J.P. Laurel	2,736	5,816	6,561
Kasilak	2,004	2,538	2,787
Katipunan	1,176	1,569	1,836
Katualan	439	697	744
Kauswagan	1,112	1,376	1,419
Kiotoy	965	1,419	1,501
Little Panay	1,562	2,015	2,434
Lower Panaga (Roxas)	1,171	1,086	1,522
Mabunao	1,837	1,592	1,912
Maduao	1,922	2,710	3,114
Malativas	2,207	2,364	2,401
Manay	4,135	4,580	5,406
Nanyo	2,903	3,599	3,847
New Malaga (Dalisay)	1,319	1,724	1,835
New Malitbog	2,173	3,040	3,276
New Pandan (Pob.)	6,147	7,882	6,636
New Visayas	13,239	15,979	16,566
Quezon	2,960	4,186	4,649
Salvacion	5,463	8,537	9,521
San Francisco (Pob.)	11,444	14,156	12,832
San Nicolas	1,558	1,852	2,071
San Roque	511	540	480
San Vicente	7,882	13,049	14,449
Santa Cruz	928	1,005	1,221
Santo Niño (Pob.)	5,431	5,968	4,332
Sindaton	2,358	1,955	3,396
Southern Davao	3,628	8,087	9,021
Tagpore	1,017	1,500	1,643
Tibungol	1,562	1,590	1,664
Upper Licanan	1,131	1,516	1,588
Waterfall	683	771	971
San Pedro	3,983	3,826	4,193

Source: Philippine Statistics Authority, *2000 and 2010 Census of Population and Housing and 2015 Census of Population*

Table 3. Population of Island Garden City of Samal
(Based on the 2000, 2010, and 2015 Censuses)

Barangay	Total Population		
	2000	2010	2015
Adecor	1,961	1,839	1,884
Anonang	1,854	2,286	2,493
Aumbay	1,893	1,696	2,017
Aundanao	1,154	1,315	1,288
Balet	2,384	2,170	2,889
Bandera	1,330	1,379	1,748
Caliclic (Dangca-an)	1,637	2,265	2,383
Camudmud	1,964	2,382	2,564
Catagman	765	1,214	1,297
Cawag	2,523	2,048	2,585
Cogon	2,008	2,650	2,933
Cogon (Talicod)	2,088	1,881	2,042
Dadatan	1,162	1,304	1,421
Del Monte	1,368	1,494	1,915
Guilon	1,103	1,212	1,553
Kanaan	1,473	1,366	1,450
Kinawitnon	1,059	1,646	1,973
Libertad	2,400	2,276	2,382
Libuak	1,032	1,357	1,472
Licup	760	830	889
Limao	1,904	2,441	2,497
Linosutan	1,113	904	853
Mambago-A	1,193	1,621	1,833
Mambago-B	1,420	2,178	2,648
Miranda (Pob.)	5,022	7,209	7,113
Moncado (Pob.)	3,824	3,981	3,744
Pangubatan (Talicud I)	1,250	1,315	1,385
Peñaplata (Pob.)	5,221	6,260	6,097
Poblacion (Kaputian)	3,739	3,946	3,983
San Agustin	1,008	1,680	1,799
San Antonio	1,560	1,923	2,098
San Isidro (Babak)	1,651	2,189	2,250
San Isidro (Kaputian)	1,322	1,381	1,556
San Jose (San Lapuz)	1,360	1,796	1,754
San Miguel (Magamono)	958	1,389	1,644
San Remigio	1,926	2,154	2,187
Santa Cruz (Talicod II)	3,620	3,804	3,814
Santo Niño	1,042	1,444	1,558
Sion (Zion)	604	656	690
Tagbaobo	1,795	2,175	2,179
Tagbay	1,101	1,204	1,407
Tagbitan-ag	2,081	2,061	2,183
Tagdaliao	705	704	765
Tagpopongan	1,298	1,283	1,409
Tambo	2,133	2,944	4,371
Toril	1,841	2,622	3,128

Source: Philippine Statistics Authority, *2000 and 2010 Census of Population and Housing and 2015 Census of Population*

Average household size was 4.3 persons in 2015

- Average household size (AHS) in City of Tagum decreased from 4.3 persons in 2010 to 4.5 persons in 2015. In 2000, there were 4.89 persons, on average, per household.

Table 5. Household Population, Number of Households, and Average Household Size, City of Tagum (Based on the 2000, 2010, and 2015 Censuses)

Census Year	Household Population	Number of Households	Average Household Size
2000	178,859	36,560	4.89
2010	241,418	53,899	4.5
2015	257,594	59,989	4.3

Source: Philippine Statistics Authority, *2015 Census of Population*

Average household size was 4.3 persons in 2015

- Average household size (AHS) in Panabo City decreased from 4.3 persons in 2010 to 4.4 persons in 2015. In 2000, there were 4.92 persons, on average, per household.

Table 5. Household Population, Number of Households, and Average Household Size, Panabo City (Based on the 2000, 2010, and 2015 Censuses)

Census Year	Household Population	Number of Households	Average Household Size
2000	133,856	27,225	4.92
2010	173,946	39,125	4.4
2015	184,123	42,489	4.3

Average household size was 4.0 persons in 2015

- The average household size (AHS) in Island Garden city of Samal decreased from 4.2 persons in 2010 to 4.0 persons in 2015. In 2000, there were 4.75 persons, on average, per household.

Table 5. Household Population, Number of Households, and Average Household Size, Island Garden City of Samal (Based on the 2000, 2010, and 2015 Censuses)

Census Year	Household Population	Number of Households	Average Household Size
2000	82,562	17,388	4.75
2010	95,808	22,802	4.2
2015	104,083	26,245	4.0

Source: Philippine Statistics Authority, *2000 and 2010 Census of Population and Housing and 2015 Census of Population*

TABLE 2. Number of Occupied Housing Units, Number of Households, Household Population, and Ratio of Households and Household Population to Occupied Housing Units by Type of Building and City/Municipality: 2015

Type of Building and City/Municipality	Occupied Housing Units	Number of Households*	Household Population*	Average Household Size	Ratio of Households to Occupied Housing Units	Ratio of Household Population to Occupied Housing Units
CITY OF PANABO						
Total	41,965	42,489	184,123	4.33	1.01	4.39
Single house	35,687	36,114	158,777	4.40	1.01	4.45
Duplex	3,011	3,040	12,327	4.05	1.01	4.09
Multi-unit residential	3,217	3,282	12,810	3.90	1.02	3.98
Commercial/industrial/agricultural	24	24	95	3.96	1.00	3.96
Institutional living quarter	1	1	1	1.00	1.00	1.00
Others	2	2	13	6.50	1.00	6.50
Not Reported	23	26	100	3.85	1.13	4.35
ISLAND GARDEN CITY OF SAMAL						
Total	25,523	26,245	104,083	3.97	1.03	4.08
Single house	23,807	24,497	97,591	3.98	1.03	4.10
Duplex	1,278	1,308	4,871	3.72	1.02	3.81
Multi-unit residential	407	409	1,503	3.67	1.00	3.69
Commercial/industrial/agricultural	22	22	86	3.91	1.00	3.91
Institutional living quarter	-	-	-	-		
Others	3	3	8	2.67	1.00	2.67
Not Reported	6	6	24	4.00	1.00	4.00
CITY OF TAGUM (Capital)						
Total	59,296	59,989	257,594	4.29	1.01	4.34
Single house	50,674	51,252	224,782	4.39	1.01	4.44
Duplex	4,186	4,241	17,210	4.06	1.01	4.11
Multi-unit residential	4,269	4,326	15,013	3.47	1.01	3.52
Commercial/industrial/agricultural	110	110	395	3.59	1.00	3.59
Institutional living quarter	24	25	68	2.72	1.04	2.83
Others	2	2	2	1.00	1.00	1.00
Not Reported	31	33	124	3.76	1.06	4.00

Table 11--*Continued*

Highest Grade/Year Completed, Sex, and City/Municipality	Age						
	17	18	19	20-24	25-29	30-34	35 and Over
CITY OF TAGUM (Capital)							
Both sexes	5,346	5,458	5,248	26,080	23,401	20,304	86,672
No grade completed	14	16	14	100	77	63	611
Preschool	2	-	3	6	-	-	9
Special education	2	5	2	12	9	2	1
Elementary	458	468	443	2,405	2,322	2,317	21,040
1st - 4th grade	108	120	136	625	576	568	5,516
5th - 6th grade	92	101	82	461	431	389	2,888
Graduate	258	247	225	1,319	1,315	1,360	12,636
High school	3,072	2,493	2,283	11,460	10,515	8,912	33,467
Undergraduate	1,202	815	672	3,007	2,787	2,383	10,650
Graduate	1,870	1,678	1,611	8,453	7,728	6,529	22,817
Postsecondary	40	130	237	1,722	1,701	1,055	2,547
Undergraduate	39	22	14	93	68	46	78
Graduate	1	108	223	1,629	1,633	1,009	2,469
College undergraduate	1,758	2,346	2,174	6,053	3,707	3,174	11,202
Baccalaureate/college graduate	-	-	92	4,310	5,040	4,714	17,352
Post baccalaureate	-	-	-	12	30	67	443
Not stated	-	-	-	-	-	-	-

Table 11--*Continued*

Highest Grade/Year Completed, Sex, and City/Municipality	Age						
	17	18	19	20-24	25-29	30-34	35 and Over
CITY OF PANABO							
Both sexes	3,465	3,492	3,405	16,872	16,369	14,496	60,788
No grade completed	15	10	15	47	61	50	380
Preschool	-	-	-	2	1	-	4
Special education	2	3	1	10	10	3	7
Elementary	332	344	337	1,830	1,852	1,903	17,127
1st - 4th grade	116	80	87	484	455	501	4,523
5th - 6th grade	58	64	57	296	294	283	2,168
Graduate	158	200	193	1,050	1,103	1,119	10,436
High school	2,209	1,904	1,736	8,657	8,572	7,335	26,385
Undergraduate	902	687	477	2,393	2,369	2,092	8,638
Graduate	1,307	1,217	1,259	6,264	6,203	5,243	17,747
Postsecondary	4	37	51	559	708	466	1,449
Undergraduate	4	9	4	17	17	11	41
Graduate	-	28	47	542	691	455	1,408
College undergraduate	903	1,193	1,186	3,372	2,347	2,038	6,662
Baccalaureate/college graduate	-	-	79	2,391	2,796	2,679	8,637
Post baccalaureate	-	-	-	3	17	18	116
Not stated	-	1	-	1	5	4	21

Table 11--*Continued*

Highest Grade/Year Completed, Sex, and City/Municipality	Age						
	17	18	19	20-24	25-29	30-34	35 and Over
ISLAND GARDEN CITY OF SAMAL							
Both sexes	1,995	1,798	1,784	8,774	8,158	6,853	37,208
No grade completed	11	9	10	53	54	42	544
Preschool	-	-	-	2	2	-	2
Special education	1	3	1	5	2	1	3
Elementary	247	249	250	1,342	1,490	1,375	16,703
1st - 4th grade	72	85	92	472	477	469	6,267
5th - 6th grade	60	58	49	264	269	262	2,779
Graduate	115	106	109	606	744	644	7,657
High school	1,303	1,042	1,020	4,892	4,593	3,691	13,760
Undergraduate	561	349	329	1,352	1,427	1,234	5,715
Graduate	742	693	691	3,540	3,166	2,457	8,045
Postsecondary	7	10	35	256	252	133	494
Undergraduate	6	6	4	25	18	14	27
Graduate	1	4	31	231	234	119	467
College undergraduate	425	484	446	1,412	865	833	2,693
Baccalaureate/college graduate	-	-	22	810	897	772	2,940
Post baccalaureate	-	-	-	2	3	6	68
Not stated	1	1	-	-	-	-	1

TABLE 3A Number of Families by Tenure Status of Dwelling Unit and Lot and by Region: 2015
(Estimates are in thousands.)

Region	Number of Families	Tenure Status of the Dwelling Unit: Own or owner-like possession of house and lot	Rent house/ room including lot	Own house rent lot	Own house rent-free lot with consent of owner	Own house rent-free lot without consent of owner	Rent-free house and lot with consent of owner	Rent-free house and lot without consent of owner	Not Applicable
Philippines	22,730	15,903	1,535	218	3,222	603	1,158	60	30
NCR	3,019	1,696	673	20	152	222	233	19	5
CAR	402	338	24	-	15	2	22	0	0
I - Ilocos Region	1,170	919	21	0	126	7	87	1	8
II - Cagayan Valley	816	779	3	-	19	2	11	1	-
III - Central Luzon	2,507	2,067	137	7	178	22	90	4	1
IVA - CALABARZON	3,251	2,271	330	11	412	44	179	3	-
IVB - MIMAROPA	697	516	29	2	85	20	44	1	1
V - Bicol Region	1,262	828	16	17	315	20	62	2	-
VI - Western Visayas	1,699	996	30	32	518	63	56	2	2
VII - Central Visayas	1,672	1,191	88	20	253	49	68	3	-
VIII - Eastern Visayas	976	617	16	22	260	17	41	1	1
IX - Zamboanga Peninsula	824	558	21	23	160	23	37	1	1
X - Northern Mindanao	1,029	702	34	11	194	24	58	6	1
XI - Davao Region	1,156	787	63	16	183	16	90	2	-
XII - SOCCSKSARGEN	1,055	755	36	14	172	21	51	5	1
ARMM	616	478	1	1	74	35	12	7	8
Caraga	579	405	13	20	107	16	18	1	0

Note: Details may not add up to total due to rounding.
Source: PSA, 2015 Family Income and Expenditure Survey

Table 1. Percentage of OSCY Among Family Members 6 to 24 Years Old by Sex: Philippines, 2017

Sex/Age Group	Family members 6 to 24 Years Old ('000)	Proportion of OSCY	Distribution of OSCY by Sex and Age Group
Both Sexes	39,214	9.1	100.0
Male	20,080	6.5	36.7
Female	19,134	11.8	63.3
Age Group			
6 to 11	12,832	1.6	5.7
12 to 15	8,507	4.7	11.2
16 to 24	17,875	16.6	83.1

Source: Philippine Statistics Authority, 2017 Annual Poverty Indicators Survey
OSCY - Out of School Child and Youth

TABLE 4 Annual Labor Force Participation, Employment, Unemployment and Underemployment Rates by Region: 2017 and 2018

(Annual estimates based on the average of the four quarter rounds of 2017 and 2018 LFS)

Region	Population 15 Years Old and Over (in thousands)		Annual Estimates							
			Labor Force Participation Rate		Employment Rate		Unemployment Rate		Underemployment Rate	
	2018	2017	2018	2017	2018	2017	2018	2017	2018	2017
Philippines	71,339	69,891	60.9	61.2	94.7	94.3	5.3	5.7	16.4	16.1
National Capital Region (NCR)	9,187	9,087	60.3	61.1	93.4	92.6	6.6	7.4	7.2	9.3
Cordillera Administrative Region (CAR)	1,270	1,241	61.9	62.7	95.9	95.7	4.1	4.3	15.2	14.8
Region I (Ilocos Region)	3,520	3,470	61.7	58.9	93.2	91.1	6.8	8.9	22.1	19.9
Region II (Cagayan Valley)	2,402	2,366	63.9	63.4	97.0	96.8	3.0	3.2	19.5	13.6
Region III (Central Luzon)	7,889	7,752	59.9	58.7	94.2	93.4	5.8	6.6	11.4	11.4
Region IV-A (CALABARZON)	10,096	9,787	62.7	63.7	93.4	93.0	6.6	7.0	13.4	14.0
MIMAROPA Region	2,093	2,047	62.0	64.0	95.3	95.2	4.7	4.8	20.6	23.7
Region V (Bicol Region)	4,113	4,017	60.9	60.1	95.1	95.4	4.9	4.6	29.6	27.6
Region VI (Western Visayas)	5,459	5,354	61.2	61.6	94.7	94.6	5.3	5.4	18.6	16.7
Region VII (Central Visayas)	5,296	5,193	61.3	65.0	94.7	95.5	5.3	4.5	17.8	17.5
Region VIII (Eastern Visayas)	3,155	3,084	61.2	60.3	95.8	95.6	4.2	4.4	21.4	22.6
Region IX (Zamboanga Peninsula)	2,617	2,559	56.3	58.5	95.9	96.0	4.1	4.0	18.9	17.3
Region X (Northern Mindanao)	3,314	3,254	66.3	63.8	95.9	94.7	4.1	5.3	20.8	18.6
Region XI (Davao Region)	3,505	3,438	60.3	62.7	95.7	95.1	4.3	4.9	15.4	17.8
Region XII (SOCCSKSARGEN)	3,150	3,086	61.7	62.2	96.1	96.0	3.9	4.0	17.0	17.9
Region XIII (Caraga)	1,885	1,844	64.4	62.1	96.0	94.9	4.0	5.1	25.4	23.1
Autonomous Region in Muslim Mindanao (ARMM)	2,390	2,311	46.6	46.1	96.3	96.6	3.7	3.4	8.4	7.0

Notes: The methodology for the computation of annual estimates of labor and employment indicators is based on PSA Board Resolution No. 01, Series of 2017-151- *Approving and Adopting the Official Methodology for Generating Annual Labor And Employment Estimates,* using the average estimates of the four LFS rounds.
The annual estimates were based on the final results of the 2017 LFS, and January and April rounds of 2018 LFS and preliminary results of the July and October rounds of 2018 LFS.

Source: Philippine Statistics Authority, Annual Labor and Employment Estimates for 2017 and 2018

TABLE 2 Percent Distribution of Population 15 Years Old and Over by Employment Status by Region and Sex: 2017

ANNUAL ESTIMATES

Region and Sex	Population 15 Years Old and Over	In the Labor Force	Employed	Unemployed	Not in the Labor Force
XI - Davao Region	3,438	2,157	2,052	105	1,281
Number (in thousand)					
Total	100.0	100.0	100.0	100.0	100.0
Male	51.3	64.8	65.0	61.1	28.5
Female	48.7	35.2	35.0	38.9	71.5

Notes: The use of the average estimates of the four-quarter rounds of the LFS data was based on PSA Board Resolution No. 01, Series of 2017-151- *Approving and Adopting the Official Methodology for Generating Annual Labor and Employment Estimates.*

Details may not add up to totals due to rounding.

Source: Philippine Statistics Authority, Annual Labor and Employment Estimates for 2017.

TABLE 2 Percent Distribution of Population 15 Years Old and Over by Employment Status by Region and Sex: April 2018

Region and Sex	Total Population 15 Years Old and Over	Total Labor Force	Employed	Unemployed	Not in the Labor Force
Region XI (Davao Region)	3,488	2,079	1,967	112	1,409
Number (in thousands)					
Total	100.0	100.0	100.0	100.0	100.0
Male	51.4	64.8	64.9	63.3	31.7
Female	48.6	35.2	35.1	36.7	68.3

Note: Details may not add up to totals due to rounding.
Source: Philippine Statistics Authority, *April 2018 Labor Force Survey*

Table 2.9A
ANNUAL PER CAPITA POVERTY THRESHOLDS AND POVERTY INCIDENCE AND MAGNITUDE OF POOR FAMILIES BY REGION
2012 and 2015
(Threshold in Pesos; Incidence in Percent)

Province	Annual Per Capita Poverty Thresholds 1/		Poverty Incidence Among Families 2/		Magnitude of Poor Families 3/	
	2012	2015	2012	2015	2012	2015
Philippines	**18,935**	**21,753**	**19.7**	**16.5**	**4,214,921**	**3,746,513**
NCR	20,344	25,007	2.6	2.7	76,530	80,246
CAR	19,483	21,770	17.5	14.9	65,516	59,759
Region I	18,373	20,488	14.0	9.6	154,712	112,233
Region II	19,125	21,860	17.0	11.7	130,965	95,367
Region III	18,188	23,200	10.1	8.9	240,079	223,684
Region IV-A	19,137	22,121	8.3	6.7	256,839	216,461
Region IV-B	17,292	20,224	23.6	17.4	150,486	121,283
Region V	18,257	21,476	32.3	27.5	375,974	346,965
Region VI	18,029	21,070	22.8	16.6	365,040	281,826
Region VII	18,767	21,914	25.7	23.6	405,694	394,336
Region VIII	18,076	21,304	37.4	30.7	337,221	299,897
Region IX	18,054	20,925	33.7	26.0	259,749	214,011
Region X	19,335	22,345	32.8	30.3	320,113	311,552
Region XI	19,967	22,754	25.0	16.6	268,957	192,449
Region XII	18,737	21,025	37.1	30.5	366,169	321,286
Caraga	19,629	22,570	31.9	30.8	169,522	178,160
ARMM	20,517	21,563	48.7	48.2	271,355	296,999

1/ The annual per capita income required or the amount to be spent to satisfy the nutritional requirements (2,000 calories) and other basic needs.
2/ The proportion of poor families to the total number of families.
3/ The total number of poor families.

Source: Philippine Statistics Authority

Table 2.9B
ANNUAL PER CAPITA POVERTY THRESHOLDS AND POVERTY INCIDENCE AND MAGNITUDE OF POOR POPULATION BY REGION
2012 and 2015
(Threshold in Pesos; Incidence in Percent)

Province	Annual Per Capita Poverty Thresholds 1/		Poverty Incidence Among Population 2/		Magnitude of Poor Population 3/	
	2012	2015	2012	2015	2012	2015
Philippines	**18,935**	**21,753**	**25.2**	**21.6**	**23,745,895**	**21,927,009**
NCR	20,344	25,007	3.9	3.9	460,831	494,630
CAR	19,483	21,770	22.8	19.7	373,740	351,590
Region I	18,373	20,488	18.5	13.1	876,650	671,087
Region II	19,125	21,860	22.1	15.8	716,754	553,616
Region III	20,071	23,200	12.9	11.2	1,340,361	1,242,071
Region IV-A	19,137	22,121	10.9	9.1	1,425,774	1,287,966
Region IV-B	17,292	20,224	31.0	24.4	876,238	754,222
Region V	18,257	21,476	41.1	36.0	2,276,848	2,172,415
Region VI	18,029	21,070	29.1	22.4	2,088,471	1,728,397
Region VII	18,767	21,914	30.2	27.6	2,094,911	2,057,479
Region VIII	18,076	21,304	45.2	38.7	1,882,934	1,756,744
Region IX	18,054	20,925	40.1	33.9	1,409,819	1,274,657
Region X	19,335	22,345	39.5	36.6	1,759,570	1,720,472
Region XI	19,967	22,754	30.7	22.0	1,411,063	1,092,200
Region XII	18,737	21,025	44.7	37.3	1,895,820	1,716,649
Caraga	19,629	22,570	40.3	39.1	1,001,923	1,062,312
ARMM	20,517	21,563	55.8	53.7	1,854,188	1,990,503

1/ The annual per capita income required or the amount to be spent to satisfy the nutritional requirements (2,000 calories) and other basic needs.
2/ The proportion of poor population to the total number of population.
3/ The total number of poor population.

Source: Philippine Statistics Authority

Table 2.10
POVERTY STATISTICS FOR THE BASIC SECTOR, REGION XI
2006, 2009, 2012 and 2015

Basic Sector	Poverty Estimates											
	2006			2009			2012			2015		
	Poverty Incidence	CV	Magnitude of Poor	Poverty Incidence	CV	Magnitude of Poor	Poverty Incidence	CV	Magnitude of Poor	Poverty Incidence	CV	Magnitude of Poor
Women	29.8	7.7	586,363	30.6	6.8	602,120	29.4	7.3	...	22.6	7.8	...
Youth	23.4	9.6	266,531	24.7	8.4	289,217	26.6	8.9	...	19.1	8.8	...
Children	39.9	6.5	679,631	40.8	6.2	683,295	40.8	5.7	...	31.7	6.9	...
Senior Citizens	20.4	12.1	55,805	20.6	10.9	63,380	19.2	11.8	...	13.3	12.2	...
Urban Poor	18.9	13.8	307,593	20.0	12.0	303,303	19.7	10.5	...	11.9	12.4	...
Migrant & Formal Sector Workers	16.9	9.7	136,810	19.3	7.1	169,220	20.1	9.2	...	12.8	8.8	...
Farmers	44.0	8.5	114,133	44.7	11.0	121,100	45.2	8.7	...	29.3	11.6	...
Fishermen	46.3	16.3	11,270	43.0	17.9	15,252	36.5	27.1	...	43.8	20.4	...
Self-employed and Unpaid Family Workers	35.4	8.5	228,138	34.9	10.8	231,838	34.9	9.1	... ...	22.1	11.4	... ...
Employed	25.4	8.8	401,825	25.7	8.2	432,718	25.5	8.5	...	16.5	8.8	...
Unemployed	24.3	13.3	26,412	17.8	15.2	19,607	27.3	14.1	...	18.1	29.7	...

Notes:
CV - Coefficient of Variation
Women - Individuals whose declared sex is female.
Youth - Persons 15 to 30 years old.
Children - Persons below 18 years old.
Senior Citizens - Persons 60 years old and above.
Urban Poor - An individual residing in an urban area whose income falls below the official poverty threshold.
Migrant Workers - Individuals who are overseas Filipino workers (OFW).
Formal Sector Workers - Employed persons working for private establishments and government organizations and corporations.
Farmers - Employed household members 15 years old and over whose primary occupation is farming and plant growing, or animal production.
Fishermen - Employed household members 15 years old and over whose primary occupation is fishing.
Self-employed and unpaid family workers - Employed individuals 15 years old and over who are either self-employed or worked without pay on family owned farm or business.
Employed - Individuals who are 15 years old and over, who during the reference period are reported either at work or with a job but not at work.
Unemployed - Individuals who are 15 years old and over, who during the reference period are reported without work and currently available for work and seeking work.
Source: Philippine Statistics Authority

Table 4--*Continued*

Age Group and City/Municipality	Both Sexes	Male	Female
NEW CORELLA			
All Ages	54,844	28,843	26,001
Under 1	1,126	600	526
1 - 4	4,777	2,488	2,289
5 - 9	6,077	3,154	2,923
10 - 14	5,658	2,919	2,739
15 - 19	5,210	2,811	2,399
20 - 24	5,113	2,657	2,456
25 - 29	4,796	2,537	2,259
30 - 34	4,019	2,170	1,849
35 - 39	3,541	1,923	1,618
40 - 44	3,029	1,632	1,397
45 - 49	2,816	1,500	1,316
50 - 54	2,468	1,281	1,187
55 - 59	1,939	1,040	899
60 - 64	1,532	797	735
65 - 69	1,093	564	529
70 - 74	718	350	368
75 - 79	539	259	280
80 years and over	393	161	232
0 - 4 years	5,903	3,088	2,815
0 - 14 years	17,638	9,161	8,477
15 - 64 years	34,463	18,348	16,115
18 years and over	33,984	17,901	16,083
60 years and over	4,275	2,131	2,144
65 years and over	2,743	1,334	1,409
CITY OF PANABO			
All Ages	184,599	93,696	90,903
Under 1	4,034	2,081	1,953
1 - 4	16,150	8,168	7,982
5 - 9	19,696	10,161	9,535
10 - 14	18,659	9,500	9,159
15 - 19	17,535	8,787	8,748
20 - 24	16,872	8,528	8,344
25 - 29	16,369	8,372	7,997
30 - 34	14,496	7,546	6,950
35 - 39	12,643	6,605	6,038
40 - 44	10,576	5,419	5,157
45 - 49	9,423	4,796	4,627
50 - 54	8,012	4,011	4,001
55 - 59	7,105	3,544	3,561
60 - 64	5,591	2,712	2,879
65 - 69	3,297	1,662	1,635
70 - 74	1,913	875	1,038
75 - 79	1,217	530	687
80 years and over	1,011	399	612
0 - 4 years	20,184	10,249	9,935
0 - 14 years	58,539	29,910	28,629
15 - 64 years	118,622	60,320	58,302
18 years and over	115,422	58,429	56,993
60 years and over	13,029	6,178	6,851
65 years and over	7,438	3,466	3,972

Table 4–*Continued*

Age Group and City/Municipality	Both Sexes	Male	Female
ISLAND GARDEN CITY OF SAMAL			
All Ages	104,123	53,711	50,412
Under 1	2,211	1,147	1,064
1 - 4	9,308	4,768	4,540
5 - 9	11,197	5,759	5,438
10 - 14	10,768	5,660	5,108
15 - 19	9,646	5,074	4,572
20 - 24	8,774	4,500	4,274
25 - 29	8,158	4,223	3,935
30 - 34	6,853	3,621	3,232
35 - 39	6,532	3,451	3,081
40 - 44	6,189	3,210	2,979
45 - 49	5,550	2,860	2,690
50 - 54	4,918	2,546	2,372
55 - 59	4,197	2,150	2,047
60 - 64	3,488	1,752	1,736
65 - 69	2,475	1,240	1,235
70 - 74	1,638	767	871
75 - 79	1,185	543	642
80 years and over	1,036	440	596
0 - 4 years	11,519	5,915	5,604
0 - 14 years	33,484	17,334	16,150
15 - 64 years	64,305	33,387	30,918
18 years and over	64,575	33,153	31,422
60 years and over	9,822	4,742	5,080
65 years and over	6,334	2,990	3,344

Table 4--*Continued*

Age Group and City/Municipality	Both Sexes	Male	Female
CITY OF TAGUM (Capital)			
All Ages	259,444	130,435	129,009
Under 1	5,144	2,667	2,477
1 - 4	21,232	10,875	10,357
5 - 9	26,237	13,605	12,632
10 - 14	24,187	12,401	11,786
15 - 19	26,187	12,905	13,282
20 - 24	26,080	12,869	13,211
25 - 29	23,401	11,727	11,674
30 - 34	20,304	10,353	9,951
35 - 39	18,173	9,359	8,814
40 - 44	15,634	8,053	7,581
45 - 49	13,597	6,870	6,727
50 - 54	11,397	5,627	5,770
55 - 59	9,431	4,592	4,839
60 - 64	7,518	3,639	3,879
65 - 69	4,794	2,288	2,506
70 - 74	2,789	1,278	1,511
75 - 79	1,803	742	1,061
80 years and over	1,536	585	951
0 - 4 years	26,376	13,542	12,834
0 - 14 years	76,800	39,548	37,252
15 - 64 years	171,722	85,994	85,728
18 years and over	167,163	83,199	83,964
60 years and over	18,440	8,532	9,908
65 years and over	10,922	4,893	6,029

Exchange Rates > Philippine Peso per US Dollar

Frequency: **Daily**

Conversion: **None**

Range: **1979 - 2018**

						2018						
Day	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1	..	51.3410	52.0700	..	..	52.5540	..	53.1600	..	54.1020	..	..
2	..	51.4910	52.0150	52.2500	51.7340	..	53.4040	53.1150	..	54.0950	..	..
3	49.9580	..	..	52.1350	51.8670	..	53.3900	53.0080	53.4750	54.2510	..	52.3890
4	49.8570	..	..	52.0260	51.8600	52.5940	53.4320	..	53.5040	54.2260	..	52.3350
5	49.8790	51.6560	51.8640	52.0590	..	52.5780	53.3430	..	53.5300	54.3450	53.5270	52.5420
6	..	51.5490	51.9430	52.1280	..	52.5330	53.4100	53.1460	53.5470	..	53.2690	52.7060
7	..	51.5500	51.9260	..	51.6470	52.3600	..	53.0400	53.6840	..	53.1470	52.8100
8	49.7690	51.2070	52.0290	..	51.8050	52.4590	..	52.9220	..	54.2810	52.9920	..
9	50.0000	51.3030	52.0160	..	51.8870	..	53.4120	53.0250	..	54.2320	52.6350	..
10	50.2320	..	..	52.0840	52.0080	..	53.3590	53.1070	53.8310	54.1660	..	52.6560
11	50.3810	..	..	51.9920	51.8870	52.6500	53.4640	..	53.8540	54.1710	..	52.7860
12	50.3780	51.6510	52.0940	51.9350	..	..	53.5160	..	53.9240	54.2380	52.9230	52.8440
13	..	51.6510	52.0080	52.0170	..	52.9020	53.5240	53.1360	54.0090	..	53.2030	52.6650
14	..	51.9160	52.0380	..	..	53.1220	..	53.3070	54.0040	..	53.1940	52.6150
15	50.3010	52.0240	52.0560	..	52.0980	..	..	53.4510	..	54.0810	53.0470	..
16	50.3500	..	52.0730	51.9890	52.4010	..	53.4700	53.4990	..	54.1300	52.9140	..
17	50.4540	..	..	52.0270	52.2860	..	53.5220	53.4430	54.0110	54.0440	..	52.7600
18	50.6500	..	..	52.0720	52.2540	53.3130	53.4660	..	54.2070	53.8910	..	53.0080
19	50.7550	52.0050	52.0020	52.0970	..	53.4580	53.4690	..	54.1020	53.9990	52.6800	52.9730
20	..	52.3540	52.0410	52.0650	..	53.3950	53.5200	53.4140	54.0600	..	52.6000	53.0260
21	..	52.2330	52.1120	..	52.3200	53.3890	..	..	54.0160	..	52.5330	53.1730
22	50.6890	52.1240	52.0760	..	52.4100	53.4190	..	53.3860	..	53.8780	52.5000	..
23	50.8350	52.1160	52.1580	52.1370	52.3130		53.5150	53.3950	..	53.7330	52.2770	..
24	51.0080	..	..	52.1730	52.3730		53.4460	53.4880	54.0270	53.8710		..
25	51.0210	..	..	52.3030	52.5330	53.3490	53.4930	..	54.2110	53.7370		..
26	50.8190	51.8930	52.3380	52.2870	..	53.4050	53.3810	..	54.3220	53.7890	52.3910	..
27		51.8290	52.2860	52.2310	..	53.4210	53.3540	..	54.2690	..	52.3940	53.0620
28		52.0340	52.2070	..	52.5860	53.4823	..	53.4950	54.2510	..	52.5230	52.7240
29	50.8850	..	..	..	52.5310	53.5220	..	53.3620	..	53.7320	52.6080	..
30	51.0400	..	..	51.9650	52.6020	..	53.3710	53.4110	..	53.5990	..	..
31	51.4210	..	..	..	52.6890	..	53.2630	53.4340	..	53.6060	..	..

Exchange Rates > Philippine Peso per US Dollar

Frequency: **Daily**

Conversion: **None**

Range: **1979 - 2018**

						2017						
Day	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1	..	49.7570	50.2550	..	..	49.7610	..	50.5020	..	..	..	50.3460
2	..	49.7830	50.2910	..	49.9000	49.7810	..	50.3970	..	50.8300	51.6860	..
3	49.7690	49.7830	50.3070	50.2190	50.0540	..	50.4490	50.4220	..	51.0360	51.4880	..
4	49.7880	..	..	50.1440	49.9330	..	50.5170	50.3650	51.1710	51.1780	..	50.3210
5	49.7320	..	..	50.1580	49.9270	49.6310	50.5390	..	51.1830	50.9510	..	50.5570
6	49.5310	49.8010	50.3730	50.1630	..	49.4040	50.5210	..	51.1180	51.0180	51.2700	50.5900
7	..	49.7290	50.3790	50.1730	..	49.4680	50.6350	50.1850	51.1360	..	51.3040	50.6760
8	..	49.6710	50.3190	..	49.9050	49.5260	..	50.3100	51.0230	..	51.2350	50.7410
9	49.4660	49.8230	50.2910	..	49.8550	49.5450	..	50.3880	..	51.1180	51.3840	..
10	49.6160	49.8880	50.3770	50.1660	49.9140	..	50.6090	50.6210	..	51.1640	51.2730	..
11	49.5480	..	..	49.7790	49.9630	..	50.6630	50.6880	50.7630	51.3080	..	50.5720
12	49.5640	..	..	49.6700	49.9330	..	50.7700	..	..	51.4670	..	50.3430
13	49.5300	49.9170	50.3490	..	..	49.4900	50.5790	..	50.8900	51.3850	51.2390	50.4350
14	..	49.9250	50.2970	..	..	49.5580	50.4810	51.0090	50.9670	..	51.2320	50.4750
15	..	49.8940	50.3570	..	49.8130	49.4950	..	50.9830	51.1430	..	51.1420	50.3980
16	49.6220	49.9220	50.3180	..	49.7100	49.5250	..	51.2170	..	..	51.1160	..
17	49.8490	49.9250	50.1910	49.5300	49.6510	..	50.6230	51.4380	..	51.4820	50.9130	..
18	49.9310	..	..	49.5350	49.7420	..	50.6330	51.3010	51.2420	51.2930	..	50.4880
19	49.7600	..	..	49.6030	49.8340	49.8500	50.7590	..	51.1770	51.3870	..	50.4290
20	49.9530	49.9870	50.1540	49.7090	..	49.8590	50.8230	..	51.0360	51.4630	50.8160	50.4620
21	..	50.1820	50.1450	49.8120	..	50.0640	50.8830	..	50.8870	..	50.9400	50.3020
22	..	50.3050	50.1640	..	49.9060	50.2390	..	51.4940	51.0860	..	50.7970	50.1940
23	49.9070	50.2400	50.3010	..	49.7530	50.3270	..	51.3770	..	51.5080	50.6280	..
24	49.8480	50.2320	50.3390	49.7880	49.7850	..	50.7600	51.2020	..	51.5070	50.6140	..
25	49.8100	..	..	49.8040	49.9680	..	50.7460	51.0500	50.8560	51.5130	..	..
26	49.8460	..	..	49.7130	49.8750	..	50.6980	..	50.6290	51.7180	..	..
27	49.6950	50.1970	50.3500	49.6990	..	50.3140	50.5860	..	50.8300	51.7410	50.6850	50.2450
28		50.2670	50.1770	..	..	50.2620	50.5460	..	50.9690	..	50.6400	50.0030
29		..	50.1800	..	49.8390	50.4370	..	51.0950	51.0730	..	50.3650	49.9230
30	49.8830	..	50.2210	..	49.8000	50.4660	..	51.1590	..	51.7990	..	..
31	49.8140	..	50.1940	..	49.8670	..	50.5820	51.1660	..	..	..	..

TABLE 1.1--*Continued*

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Housing, water, electricity, gas, and other fuels	**2018**	132.2	128.2	128.5	128.6	129.0	130.1	130.7	133.1	134.3	136.9	138.3	136.8	
	2017	165.8	161.3	163.0	164.2	165.5	167.0	165.8	166.4	166.7	167.1	167.3	167.5	167.9
Furnishing, household equipment, and routine maintenance of the house	**2018**	125.5	123.6	123.8	124.4	124.6	124.7	124.8	125.7	126.3	127.2	127.4	127.6	
	2017	150.3	148.0	148.3	148.6	148.6	149.4	150.3	150.5	150.7	151.9	151.9	152.9	152.9
Health	**2018**	124.2	122.2	122.3	122.5	122.6	122.9	123.4	125.4	125.6	125.8	126.9	127.1	
	2017	174.0	170.9	172.5	173.3	173.4	173.5	173.7	174.2	174.6	174.9	175.0	176.0	176.0
Transport	**2018**	106.3	102.6	104.3	104.3	105.2	106.4	107.3	106.5	106.6	108.2	109.4	108.7	
	2017	132.8	132.3	131.9	132.2	132.4	132.7	132.4	132.2	132.8	133.4	133.3	133.6	134.3
Communication	**2018**	105.8	105.8	105.8	105.8	105.8	105.8	105.8	105.8	105.8	105.8	105.8	105.8	
	2017	100.1	99.7	99.7	99.7	100.0	100.0	100.0	100.0	100.0	100.1	100.6	100.6	100.6
Recreation and culture	**2018**	111.5	109.9	110.0	110.1	110.1	110.1	110.9	111.5	113.1	113.3	113.6	113.7	
	2017	118.7	115.6	117.7	117.7	117.8	118.7	118.7	119.4	119.5	119.5	119.5	120.4	120.4
Education	**2018**	122.4	128.1	128.1	128.1	128.1	128.1	131.2	115.1	115.0	115.0	115.0	115.0	
	2017	149.9	148.2	148.2	148.2	148.2	148.2	151.1	151.1	151.1	151.1	151.1	151.1	151.1
Restaurant and miscellaneous goods and services	**2018**	118.9	115.4	115.7	116.0	116.1	116.3	116.9	120.7	121.5	122.8	123.0	123.9	
	2017	144.2	142.1	143.0	143.1	143.5	144.1	144.3	144.6	144.8	144.9	144.9	145.3	145.5
XI - Davao Region														
All items	**2018**	118.0	115.1	115.2	115.3	116.2	116.6	117.4	118.4	119.8	121.2	121.7	120.6	
	2017	159.3	157.2	157.3	158.1	158.2	158.1	159.0	159.2	159.6	160.1	160.9	161.4	162.2
Food and non-alcoholic beverages	**2018**	119.9	117.4	117.3	117.5	118.5	118.7	118.9	119.8	122.2	123.6	123.6	121.8	
	2017	176.0	174.2	174.5	174.5	174.3	173.9	175.3	175.5	176.4	176.6	178.2	179.0	180.1
Food	**2018**	120.0	117.7	117.5	117.6	118.6	118.9	119.0	119.8	122.3	123.7	123.6	121.6	
	2017	178.8	176.9	177.2	177.2	176.9	176.6	178.0	178.3	179.1	179.4	181.1	181.9	183.0
Bread and Cereals	**2018**	117.6	113.9	114.3	115.2	116.2	116.8	117.6	118.1	120.2	122.9	121.0	117.9	
	2017	175.7	172.7	172.4	173.9	174.7	175.0	175.9	177.1	177.2	177.3	177.0	177.3	178.1
Meat	**2018**	120.2	115.5	115.8	117.1	117.9	118.4	120.1	120.6	123.5	124.8	124.5	123.7	
	2017	153.0	148.5	149.6	149.7	152.2	152.9	153.9	153.6	154.5	155.0	155.0	155.8	155.8
Fish	**2018**	121.2	122.0	119.6	117.9	121.0	119.7	115.7	117.0	122.9	123.4	127.9	125.8	
	2017	198.8	196.0	189.2	190.3	191.4	193.2	198.1	198.7	201.8	202.2	206.7	209.6	208.9
Milk, cheese, and eggs	**2018**	121.2	119.1	119.4	120.3	120.3	121.2	122.1	122.0	121.2	122.0	122.9	123.2	
	2017	155.9	156.2	156.8	156.8	156.1	155.7	154.9	155.5	155.5	155.5	155.7	156.0	156.1

Continued

TABLE 1.1--*Continued*

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Oils and fats	**2018**	119.1	116.9	117.1	117.5	118.4	118.8	119.1	119.4	119.9	120.4	121.1	121.4	
	2017	226.3	218.7	220.6	224.8	225.0	225.3	226.8	227.9	227.9	228.7	229.7	230.1	229.7
Fruit	**2018**	127.0	135.4	130.9	129.1	127.7	127.5	126.5	124.4	124.4	130.4	121.4	119.0	
	2017	211.5	210.5	210.5	210.9	212.3	210.4	204.7	204.1	204.2	211.2	220.0	219.5	219.6
Vegetables	**2018**	122.6	124.4	125.0	121.3	119.6	119.8	119.7	122.7	125.9	121.7	125.7	123.0	
	2017	217.0	223.2	238.1	229.6	214.2	205.9	210.1	208.1	210.2	207.5	214.8	215.8	226.2
Sugar, jam, honey, chocolate, and confectionery	**2018**	123.9	113.1	113.0	114.0	115.7	117.5	128.8	134.4	133.1	133.0	131.5	129.3	
	2017	141.9	149.1	147.5	144.8	143.6	141.7	140.6	140.3	139.4	139.3	139.5	139.1	138.3
Food products N.E.C.	**2018**	125.4	120.3	122.5	126.5	127.2	128.7	125.6	126.4	125.3	124.8	124.7	127.9	
	2017	166.4	161.3	164.4	164.7	167.6	170.6	169.0	167.9	166.4	164.6	165.6	167.1	167.0
Non-alcoholic beverages	**2018**	118.7	113.4	114.6	115.3	116.2	116.7	118.3	119.9	120.9	122.8	123.5	124.6	
	2017	137.5	136.3	136.7	136.9	137.2	137.3	137.4	137.6	137.9	138.1	138.2	138.3	138.3
Alcoholic beverages and tobacco	**2018**	158.5	147.2	151.4	155.8	158.1	159.1	160.3	161.0	161.9	162.7	162.9	163.1	
	2017	184.2	180.3	181.3	182.5	182.8	183.4	183.5	183.6	183.7	184.0	185.7	188.3	190.9
Clothing and footwear	**2018**	121.6	118.9	119.2	119.3	120.6	121.1	121.8	122.4	122.6	123.5	123.8	124.0	
	2017	148.9	146.0	146.6	147.3	147.8	148.1	148.9	149.5	149.9	150.2	150.4	150.7	151.1
Housing, water, electricity, gas, and other fuels	**2018**	116.4	113.2	113.1	112.4	112.7	113.4	115.1	117.7	118.3	120.6	122.2	121.4	
	2017	143.5	140.8	139.5	142.9	143.8	143.6	143.7	143.6	143.7	145.2	144.8	145.0	145.1
Furnishing, household equipment, and routine maintenance of the house	**2018**	115.4	112.9	113.1	113.3	113.5	113.9	114.7	116.1	116.3	118.1	118.5	118.5	
	2017	140.1	138.1	138.4	139.0	139.3	139.5	139.7	139.9	140.1	140.2	141.6	142.2	143.6
Health	**2018**	116.5	112.7	113.3	113.4	115.7	115.9	116.0	117.4	118.5	119.2	119.6	119.9	
	2017	160.5	157.6	158.2	159.1	159.6	160.3	161.0	161.3	161.6	161.7	162.0	162.0	162.1
Transport	**2018**	104.7	101.0	102.1	101.8	102.8	103.9	104.8	105.4	105.7	107.7	109.2	107.3	
	2017	140.3	138.1	138.6	138.9	139.5	139.7	140.4	140.2	140.6	141.5	140.7	141.5	143.4
Communication	**2018**	102.1	101.7	101.7	101.7	101.6	101.7	101.6	101.8	102.2	102.9	102.9	102.9	
	2017	94.0	93.9	93.9	93.9	93.9	93.9	94.0	94.0	94.0	94.0	94.2	94.2	94.2
Recreation and culture	**2018**	115.5	113.3	113.3	113.4	113.5	113.8	114.6	115.5	117.1	118.7	118.7	118.9	
	2017	126.3	125.2	125.4	125.4	125.5	125.8	126.2	126.2	126.6	126.7	127.2	127.5	128.3
Education	**2018**	119.7	120.2	120.2	120.2	120.2	120.2	122.8	118.5	118.5	118.5	118.5	118.5	
	2017	177.8	175.0	175.0	175.0	175.0	175.0	179.8	179.8	179.8	179.8	179.8	179.8	179.8

Continued

TABLE 1.1--*Continued*

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Restaurant and miscellaneous goods and services	**2018**	119.8	116.7	116.9	117.5	118.3	118.5	120.3	121.4	121.5	121.9	122.5	122.6	
	2017	137.2	136.0	136.4	136.8	137.0	137.1	137.3	137.4	137.5	137.6	137.9	137.9	137.9
XII - SOCCSKSARGEN														
All items	**2018**	120.5	117.4	118.0	118.2	118.6	119.1	120.2	120.8	123.0	123.4	123.4	122.9	
	2017	158.0	156.1	156.7	157.1	156.7	157.2	157.6	157.8	158.3	158.9	158.9	159.4	160.9
Food and non-alcoholic beverages	**2018**	123.4	121.0	120.5	120.8	121.2	121.5	123.3	123.6	126.4	127.2	126.7	124.9	
	2017	167.5	165.2	165.6	165.9	165.6	165.7	167.1	167.5	168.3	168.5	169.0	169.6	171.4
Food	**2018**	123.7	121.7	121.1	121.0	121.4	121.7	123.6	123.9	126.8	127.7	126.9	125.0	
	2017	170.2	167.7	168.2	168.6	168.2	168.3	169.8	170.2	171.0	171.3	171.8	172.5	174.4
Bread and Cereals	**2018**	120.4	115.2	115.9	117.6	118.2	118.9	119.7	121.9	126.0	126.4	123.7	120.4	
	2017	173.2	171.1	171.5	172.3	171.8	172.7	174.1	174.5	175.2	174.5	173.6	173.1	173.7
Meat	**2018**	119.9	118.0	118.3	118.8	119.2	120.0	120.3	120.1	120.1	120.9	121.3	121.9	
	2017	151.4	147.5	147.8	148.1	148.9	149.3	150.7	151.0	151.9	153.3	155.4	155.8	157.4
Fish	**2018**	132.5	135.5	132.0	129.6	129.6	127.6	132.9	129.0	133.1	135.3	137.3	135.1	
	2017	188.7	183.7	184.8	184.6	185.2	185.3	189.0	189.2	190.3	190.8	191.6	192.9	197.2
Milk, cheese, and eggs	**2018**	113.8	112.4	112.4	112.7	112.8	113.0	113.1	113.9	115.1	115.6	115.6	115.7	
	2017	142.6	141.8	142.0	142.2	142.2	142.3	142.4	142.5	142.7	143.2	143.3	143.2	143.3
Oils and fats	**2018**	107.0	106.5	106.8	107.0	106.8	106.4	106.5	106.8	107.1	107.2	107.9	108.5	
	2017	166.2	163.1	164.1	165.2	165.7	165.9	166.2	166.6	167.1	167.1	167.2	168.1	168.2
Fruit	**2018**	129.1	133.6	131.9	130.7	129.7	128.6	128.5	124.5	128.4	127.3	127.8	129.2	
	2017	181.5	179.9	180.0	180.3	180.7	179.9	178.5	176.8	179.3	181.1	185.5	187.4	188.9
Vegetables	**2018**	144.1	146.7	142.7	137.5	138.2	140.3	145.8	145.4	147.2	148.2	148.3	145.3	
	2017	182.8	181.0	181.8	181.5	178.3	175.0	177.1	180.1	181.1	182.4	186.3	191.2	198.3
Sugar, jam, honey, chocolate, and confectionery	**2018**	114.0	107.3	107.7	106.6	107.3	109.7	113.7	118.3	118.5	122.1	121.6	121.1	
	2017	135.3	138.5	137.3	136.2	135.6	135.1	134.8	134.8	134.8	134.6	133.8	133.7	134.1
Food products N.E.C.	**2018**	118.3	115.4	115.6	116.2	117.0	119.2	119.1	118.9	119.2	119.1	119.4	122.3	
	2017	155.9	155.9	155.9	155.7	154.9	155.9	155.8	155.7	155.4	155.5	155.7	156.8	157.0
Non-alcoholic beverages	**2018**	119.1	111.3	113.1	117.3	118.4	118.8	119.3	120.5	121.3	121.4	124.2	124.3	
	2017	128.5	128.0	128.1	128.4	128.4	128.4	128.5	128.6	128.6	128.6	128.7	129.0	129.1
Alcoholic beverages and tobacco	**2018**	200.8	184.6	194.3	198.6	198.8	199.5	199.6	201.9	206.2	206.7	207.3	210.8	
	2017	204.7	202.1	202.6	203.3	203.5	203.6	203.7	204.3	204.6	204.8	205.5	207.0	211.3

Continued

TABLE 4.4 Bank Interest Rates: 2017 and 2018

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Savings deposit	**2018**	0.842	0.798	0.670	0.758	0.747	0.811	0.795	0.877	0.896	0.983	1.081		
(Percent per annum)	**2017**	0.685	0.738	0.635	0.693	0.670	0.679	0.647	0.707	0.713	0.674	0.704	0.651	0.709
Treasury Bill Rates														
91 - day	**2018**	3.28	2.277	2.670	3.008	3.440	3.407	3.356	3.297	3.239	3.349	4.778		
182 - day		3.86	2.544	2.854	3.186	3.894	3.868	3.745	4.154	4.109	4.350	5.855		
364 - days		4.27	2.877	3.040	3.393	3.906	4.235	4.348	4.760	4.885	5.112	6.126		
all maturities		3.82	2.484	2.779	3.125	3.600	3.769	3.864	4.125	4.187	4.502	5.763		
91 - day	**2017**	2.123	1.780	2.104	2.367	2.347	2.177	2.103	2.152	2.160	2.060	1.958	2.148	-
182 - day		2.475	2.037	2.354	2.600	2.623	2.548	2.440	2.496	2.566	2.543	2.457	2.563	-
364 - days		2.826	2.276	2.697	2.781	2.970	2.901	2.860	2.968	2.951	2.891	2.837	2.952	-
all maturities		2.414	1.963	2.296	2.551	2.594	2.494	2.410	2.463	2.506	2.442	2.359	2.478	-
Time Deposit Rates														
S - T < 360 days	**2018**	2.864	2.416	2.575	2.602	2.573	2.717	2.574	3.071	3.241	3.309	3.562		
L - T > 360 days		2.795	2.548	2.640	2.768	2.224	3.251	2.566	3.039	2.756	2.962	3.195		
S - T < 360 days	**2017**	1.766	1.605	1.617	1.739	1.659	1.760	1.734	1.784	1.724	1.746	1.801	1.824	2.204
L - T > 360 days		2.822	3.130	3.106	2.956	2.789	2.825	2.829	2.780	3.027	2.598	2.575	2.489	2.757

Source: Bangko Sentral ng Pilipinas

TABLE 4.5 Bank Lending Rates: 2017 and 2018

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Bank Lending Rates	**2018**	5.976	5.726	5.353	5.842	5.749	6.025	5.901	6.199	6.212	6.149	6.602		
(Commercial Banks) WAIR in percent per annum	**2017**	5.627	5.639	5.208	5.772	5.473	5.783	5.609	5.673	5.687	5.609	5.730	5.566	5.778

WAIR - weighted average interest rates

Source: Bangko Sentral ng Pilipinas

TABLE 1.7 Inflation Rate and Purchasing Power of the Peso by Area: 2017 and 2018

(2012=100)

Indicator	Year	Average	January	February	March	April	May	June	July	August	September	October	November	December
Inflation Rate														
Philippines	**2018**	5.3	4.0	3.9	4.3	4.5	4.6	5.2	5.7	6.4	6.7	6.7	6.0	
	2017	2.9	2.7	3.1	3.1	3.2	2.9	2.5	2.4	2.6	3.4	3.1	3.0	3.3
National Capital Region	**2018**	5.7	5.4	4.7	5.2	5.2	4.9	5.8	6.5	7.0	6.3	6.1	5.6	
	2017	3.8	3.0	3.4	3.9	4.0	3.8	3.1	2.9	3.3	4.7	4.3	4.5	4.6
Areas Outside NCR	**2018**	5.2	3.5	3.7	4.1	4.3	4.6	5.1	5.5	6.2	6.8	6.8	6.2	
	2017	2.7	2.7	3.0	2.9	2.9	2.7	2.3	2.2	2.4	3.0	2.8	2.5	2.9
Purchasing Power of the Peso (1/Consumer Price Index x 100)														
Philippines	**2018**	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8	
	2017	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
National Capital Region	**2018**	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	
	2017	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Areas Outside NCR	**2018**	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8	0.8	
	2017	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6

Source: Philippine Statistics Authority

Appendix B. Social Data

List of all social indicators for each barangay used in mobile implementation.

1	location	placetype	Education,Baccalauate graduate	Education,College undergraduate	Education,Elementary	Education,High school	Education,No grade completed	Education,Not started	Education,Out of school youth	Education,Out of school youth,female	Education,Out of school youth,male	Education,Post baccalaureate	Education,Postsecondary	Education,Preschool	Education,Special education
2	PanaboCity_AOFloirendo	urban	445.5	389	613	1375.5	14.5	1	179	114.5	65.5	4	85.5	0	1
3	PanaboCity_Buenavista	urban	532	465	732	1643	17	1	214	136.5	77.5	5	102.5	0	1
4	PanaboCity_Cacao	rural	73.5	64.5	101.5	227	2	0	29.5	19	11	1	14	0	0
5	PanaboCity_Cagangohan	rural	109.5	96	151	339	4	0	44	28	16	1	21	0	0
6	PanaboCity_Consolacion	urban	1266	1106	1741.5	3907.5	41	2	508.5	324.5	185	12	244	1	2
7	PanaboCity_Dapco	rural	160.5	140	221	495.5	5	0	64.5	41	23.5	1.5	31	0	0
8	PanaboCity_DatuAbdulDadia	rural	374	326.5	514.5	1154	12	1	150	95.5	54.5	3.5	72	0	1
9	PanaboCity_Gredu	urban	1520	1328	2091.5	4692	49.5	3	610.5	390	222.5	14	293	1	3
10	PanaboCity_JPLaurel	urban	602.5	527	829.5	1861	20	1	242	154.5	88.5	6	116.5	0	1
11	PanaboCity_Kasilak	urban	256	223.5	352	790.5	8	0	102.5	65.5	37.5	2	49.5	0	0
12	PanaboCity_Katipunan	rural	169	147.5	232	521	5.5	0	67.5	43	25	2	32.5	0	0
13	PanaboCity_Katualan	rural	68.5	59.5	94.5	211	2	0	27.5	17.5	10	1	13	0	0
14	PanaboCity_Kauswagan	rural	130.5	114	179	402.5	4	0	52.5	33.5	19	1	25	0	0
15	PanaboCity_Kiotoy	rural	138	120.5	190	425.5	4.5	0	55.5	35.5	20	1	26.5	0	0
16	PanaboCity_LittlePanay	rural	223.5	195	307.5	690.5	7	0	89.5	57.5	33	2	43	0	0
17	PanaboCity_LowerPanaga	rural	140	122.5	192	431.5	5	0	56	36	20.5	1	27	0	0
18	PanaboCity_Mabunao	rural	176	153.5	241.5	542	6	0	70.5	45	26	2	34	0	0
19	PanaboCity_Maduao	rural	286.5	250	394	883	9	1	115	73.5	42	3	55	0	1
20	PanaboCity_Malativas	rural	220.5	193	303.5	681	7	0	88.5	56.5	32	2	42.5	0	0
21	PanaboCity_Manay	urban	496.5	434	683.5	1533.5	16	1	199.5	127.5	72.5	5	95.5	0	1
22	PanaboCity_Nanyo	rural	353	308.5	486.5	1091	11.5	1	142	90.5	51.5	3	68.5	0	1
23	PanaboCity_NewMalaga	rural	169	147	232	520.5	5.5	0	67.5	43	25	2	32.5	0	0
24	PanaboCity_NewMalitbog	rural	301	263	414	929	10	1	121	77.5	44	3	58	0	1
25	PanaboCity_NewPandan	urban	609.5	533	839	1882	20	1	245	156	89.5	6	117.5	0	1
26	PanaboCity_NewVisayas	urban	1522	1329.5	2094.5	4698.5	49.5	3	611.5	390	222.5	14	293.5	1	3
27	PanaboCity_Quezon	rural	427	373	588	1318.5	14	1	172	109.5	62.5	4	82.5	0	1
28	PanaboCity_Salvacion	urban	874.5	764	1203.5	2700.5	28.5	2	351	224	128	8	169	0	2
29	PanaboCity_SanFrancisco	urban	1178.5	1030	1622.5	3639.5	38.5	2	473.5	302.5	172.5	11	227.5	0.5	2
30	PanaboCity_SanNicolas	rural	190	166	261.5	587.5	6	0	76.5	49	28	2	36.5	0	0
31	PanaboCity_SanPedro	rural	44	38.5	60.5	136	1	0	18	11	6	0	8.5	0	0
32	PanaboCity_SanRoque	urban	1327.5	1159.5	1827	4098	43.5	2.5	533	340	194	12	256	1	2
33	PanaboCity_SanVicente	rural	112.5	98	154.5	346	4	0	45	29	16	1	22	0	0
34	PanaboCity_SantaCruz	urban	398	348	548	1228.5	13	1	160	102	58.5	4	76.5	0	1
35	PanaboCity_SantoNino	rural	312	272.5	429.5	963	10	1	125.5	80	45.5	3	60	0	1
36	PanaboCity_Sindaton	urban	828.5	724	1140.5	2559	27	2	333	212.5	121.5	8	160	0	1.5
37	PanaboCity_SouthernDavao	rural	151	132	208	466	5	0	60.5	38.5	22	1	29	0	0
38	PanaboCity_Tagpore	rural	153	133.5	210.5	472	5	0	61.5	39	22	1	29.5	0	0
39	PanaboCity_Tibungol	rural	146	127.5	201	450.5	5	0	58.5	37.5	21	1	28	0	0
40	PanaboCity_UpperLicanan	rural	89.5	78	122.5	275.5	3	0	36	23	13	1	17	0	0
41	PanaboCity_Waterfall	urban	385	336.5	530	1189.5	12.5	1	155	98.5	56.5	4	74.5	0	1
42	SamalCity_Adecor1	urban	102	109	393.5	507	13	0	69.5	43	26	1	21.5	0	0
43	SamalCity_Adecor2	urban	102	109	393.5	507	13	0	69.5	43	26	1	21.5	0	0
44	SamalCity_Anonang	rural	135	144.5	521	671	17	0	91.5	57.5	34	2	28	0	0
45	SamalCity_Aumbay	rural	109	117	421.5	543	14	0	74.5	46.5	27.5	2	23	0	0
46	SamalCity_Aundanao	rural	69.5	74.5	269	346.5	9	0	47.5	29.5	17.5	1	14.5	0	0
47	SamalCity_Balet1	rural	156.5	167.5	603.5	777.5	20	0	106	66.5	39.5	2	33	0	0
48	SamalCity_Balet2	rural	156.5	167.5	603.5	777.5	20	0	106	66.5	39.5	2	33	0	0
49	SamalCity_Balet3	rural	156.5	167.5	603.5	777.5	20	0	106	66.5	39.5	2	33	0	0
50	SamalCity_Bandera	rural	94.5	101.5	365	470.5	12	0	64.5	40	24	1	20	0	0
51	SamalCity_Caliclic	urban	129	138	498	641	16.5	0	87.5	54.5	32.5	2	27	0	0
52	SamalCity_Camudmud	rural	139	148.5	535.5	690	18	0	94.5	58.5	35	2	29	0	0
53	SamalCity_Catagman	rural	70.5	75.5	271	349	9	0	47.5	29.5	18	1	15	0	0
54	SamalCity_Cawag	rural	140	150	540	695.5	18	0	95	59.5	35.5	2	29.5	0	0
55	SamalCity_Cogon2	rural	159	170	613	789.5	20	0	108	67.5	40	2	33.5	0	0
56	SamalCity_Cogon1	rural	110.5	118	426.5	549.5	14	0	75	46.5	28	2	23	0	0
57	SamalCity_Dadatan	rural	77	82.5	297	382	10	0	52.5	32.5	19.5	1	16	0	0
58	SamalCity_DelMonte	rural	104	111	400	515	13	0	70.5	44	26	1.5	22	0	0

	location	placetype	Education,Baccalauate graduate	Education,College undergraduate	Education,Elementary	Education,High school	Education,No grade completed	Education,Not started	Education,Out of school youth	Education,Out of school youth,female	Education,Out of school youth,male	Education,Post baccalaureate	Education,Postsecondary	Education,Preschool	Education,Special education
59	SamalCity_Guilon	rural	84	90	324.5	418	11	0	57.5	35.5	21	1	17.5	0	0
60	SamalCity_Kanaan	rural	78.5	84	303	390	10	0	53.5	33	20	1	16.5	0	0
61	SamalCity_Kinawitnon	rural	107	114	412	531	14	0	72.5	45.5	27	2	22.5	0	0
62	SamalCity_Libertad	rural	129	138	498	641	16.5	0	87.5	54.5	32.5	2	27	0	0
63	SamalCity_Libuak	rural	79.5	85.5	307.5	396	10	0	54.5	33.5	20	1	17	0	0
64	SamalCity_Licup	rural	48.5	51.5	185.5	239	6	0	32.5	20.5	12	1	10	0	0
65	SamalCity_Limao	rural	135	145	522	672	17	0	92	57.5	34	2	28.5	0	0
66	SamalCity_Linosutan	rural	46.5	49.5	178.5	229.5	6	0	31.5	19.5	12	1	10	0	0
67	SamalCity_MambagoA	rural	99	106	383	493	13	0	67.5	42	25	1	21	0	0
68	SamalCity_MambagoB	rural	143.5	153.5	553.5	712.5	18	0	97.5	60.5	36.5	2	30	0	0
69	SamalCity_Miranda	urban	385	412.5	1486	1914	49.5	0	261.5	163	97.5	6	80.5	0	1
70	SamalCity_Moncado	rural	202.5	217	782	1008	26	0	138	85.5	51.5	3	42.5	0	0
71	SamalCity_Pangubatan	rural	75	80.5	289.5	373	10	0	51	31.5	19	1	16	0	0
72	SamalCity_Penaplata	urban	330.5	353.5	1274	1641	42.5	0	224	140	83.5	5	69.5	0	1
73	SamalCity_Poblacion	rural	215.5	231	832.5	1071.5	27.5	0	146.5	91.5	54.5	3	45.5	0	0
74	SamalCity_SanAgustin	rural	97.5	104	376	484	12.5	0	66.5	41.5	24.5	1	20.5	0	0
75	SamalCity_SanAntonio	rural	113.5	122	438.5	564.5	14.5	0	77.5	48	29	2	24	0	0
76	SamalCity_SanIsidro1	rural	122	130	470	605.5	15.5	0	82.5	51.5	31	2	25.5	0	0
77	SamalCity_SanIsidro2	rural	84.5	90.5	325.5	418.5	11	0	57.5	35.5	21	1	18	0	0
78	SamalCity_SanJose	rural	95	101.5	366.5	472	12	0	64.5	40	24	1	20	0	0
79	SamalCity_SanMiguel	rural	89	95.5	343.5	442.5	11	0	60.5	37.5	22.5	1	18.5	0	0
80	SamalCity_SanRemigio	rural	118	127	457	588.5	15	0	80.5	50	30	2	25	0	0
81	SamalCity_SantaCruz	rural	206.5	221	797	1026.5	26.5	0	140	87.5	52.5	3	43.5	0	0
82	SamalCity_SantoNino	rural	84.5	90.5	325.5	419.5	11	0	57.5	35.5	21.5	1	18	0	0
83	SamalCity_Sion	rural	37.5	40	144	185.5	5	0	25.5	16	9.5	1	8	0	0
84	SamalCity_Tagbaobo	rural	118	126	455.5	586.5	15	0	80	50	30	2	25	0	0
85	SamalCity_Tagbay	rural	76.5	81.5	294	379	10	0	51.5	32	19	1	16	0	0
86	SamalCity_TagbitanAg	rural	118	127	456	587.5	15	0	80.5	50	30	2	25	0	0
87	SamalCity_Tagdaliao	rural	41.5	44.5	160	206	5	0	28	17.5	10.5	1	9	0	0
88	SamalCity_Tagpopongan	rural	76.5	81.5	294.5	379	10	0	51.5	32.5	19	1	16	0	0
89	SamalCity_Tambo1	rural	237	253	913	1176.5	30.5	0	160.5	100	59.5	3	49.5	0	0
90	SamalCity_Tambo2	rural	237	253	913	1176.5	30.5	0	160.5	100	59.5	3	49.5	0	0
91	SamalCity_Toril	rural	169.5	181.5	653.5	841.5	21.5	0	115	71.5	42.5	2	35.5	0	0
92	TagumCity_Apokon	urban	3717.5	2856	3323.5	7615.5	100.5	0	1107	712.5	400.5	65.5	831.5	2	3
93	TagumCity_Bincungan	rural	528.5	406	472	1082	14	0	157	101.5	56.5	9	118	0	0
94	TagumCity_Busaon	rural	356	273.5	318	729	10	0	106	68.5	38.5	6	79.5	0	0
95	TagumCity_Canocotan	urban	1017	781	909	2083	27.5	0	303	195	109.5	18	227.5	0	1
96	TagumCity_Cuambogan	urban	1326.5	1019.5	1185.5	2717	36	0	395.5	254.5	143	23	297	1	1
97	TagumCity_LaFilipina	urban	1924	1478	1720	3941	52	0	573	368.5	207	34	430	1	1
98	TagumCity_Liboganon	rural	285	218.5	254.5	583.5	8	0	84.5	54.5	30.5	5	63.5	0	0
99	TagumCity_Madaum1	urban	1340.5	1029.5	1198	2745.5	36.5	0	399.5	256.5	144	23.5	300	1	1
100	TagumCity_Madaum2	urban	1340.5	1029.5	1198	2745.5	36.5	0	399.5	256.5	144	23.5	300	1	1
101	TagumCity_Magdum	urban	1277	981	1141.5	2615.5	34.5	0	380.5	244.5	137.5	22.5	285.5	1	1
102	TagumCity_Mankilam	urban	4870	3741.5	4353.5	9976.5	132	0	1450.5	933	524	85.5	1089	2	4
103	TagumCity_NewBalamban	rural	183	140.5	164	374.5	5	0	54.5	35	20	3	41	0	0
104	TagumCity_NuevaFuerza	rural	244	187.5	218.5	500	7	0	72.5	46.5	26	4	54.5	0	0
105	TagumCity_Pagsabangan	rural	656	504	586.5	1344.5	18	0	195.5	126	70.5	11.5	147	0	0.5
106	TagumCity_Pandapan	rural	298	229.5	266.5	611	8	0	88.5	57.5	32	5	66.5	0	0
107	TagumCity_MagugpoPoblacion	urban	395.5	304	353.5	810.5	11	0	118	75.5	42.5	7	88.5	0	0
108	TagumCity_SanAgustin	rural	139	107	124.5	285.5	4	0	41.5	27	15	2	31	0	0
109	TagumCity_SanIsidro	rural	599.5	460.5	536	1228	16	0	178.5	115	64.5	10.5	134	0	0
110	TagumCity_SanMiguel	urban	2164.5	1663	1935	4434	58.5	0	645	414.5	232.5	38	484	1	2
111	TagumCity_VisayanVillage	urban	5037	3869.5	4502.5	10318.5	136.5	0	1500.5	965	542	88.5	1126.5	2	4
112	TagumCity_MagugpoEast	urban	1803.5	1385.5	1612	3694.5	49	0	537.5	345.5	194	31.5	403.5	1	1
113	TagumCity_MagugpoNorth	urban	1168	897.5	1044	2392.5	31.5	0	348	223.5	125.5	20.5	261.5	1	1
114	TagumCity_MagugpoSouth	urban	1354	1040.5	1210.5	2773.5	36.5	0	403.5	259.5	146	24	303	1	1
115	TagumCity_MagugpoWest	urban	1746	1341.5	1560.5	3575.5	47.5	0	520	334.5	188	30.5	390.5	1	1

1	location	Household, number of households	Housing,dwelling tenure status,Own house rent lot	Housing,dwelling tenure status,Own house rent,free lot with consent of owner	Housing,dwelling tenure status,Own house rent,free lot without consent of owner	Housing,dwelling tenure status,Own or owner,like possession of house and lot	Housing,dwelling tenure status,Rent house/ room including lot	Housing,dwelling tenure status,Rent, free house and lot with consent of owner	Housing,dwelling tenure status,Rent, free house and lot without consent of owner	Labor,Employed	Labor,In the Labor Force	Labor,Not in the Labor Force
2	PanaboCity_AOFloirendo	1158.5	16.5	183	16	788.5	63	90.5	2	1974.5	2081	1321.5
3	PanaboCity_Buenavista	1384.5	20	219	19	942	75.5	107.5	2	2359.5	2486.5	1579
4	PanaboCity_Cacao	191	3	30	3	130	10	15	0	325.5	343	218
5	PanaboCity_Cagangohan	285.5	4	45	4	194.5	15.5	22	0	487	513.5	326
6	PanaboCity_Consolacion	3292	46.5	520	45.5	2240	179	256	5	5610.5	5913	3755
7	PanaboCity_Dapco	417.5	6	66	6	284.5	23	32.5	1	711.5	750	476
8	PanaboCity_DatuAbdulDadia	972	14	153.5	13	661.5	53	75.5	1	1657	1746	1109
9	PanaboCity_Gredu	3953.5	56	624.5	54.5	2689.5	215.5	307.5	6	6737.5	7100	4509
10	PanaboCity_JPLaurel	1568	22	247.5	21.5	1067	85.5	122	2	2672	2816	1788.5
11	PanaboCity_Kasilak	666	9.5	105.5	9	453.5	36	52	1	1135	1196	760
12	PanaboCity_Katipunan	438.5	6	69.5	6	298.5	24	34	1	748	788	500
13	PanaboCity_Katualan	178	3	28	2	121	10	14	0	303	319.5	202.5
14	PanaboCity_Kauswagan	339	5	53.5	5	230.5	18.5	26.5	0	578	609	387
15	PanaboCity_Kiotoy	359	5	56.5	5	244	19.5	28	1	611	644	409
16	PanaboCity_LittlePanay	582	8	91.5	8	396	32	45	1	991.5	1044.5	663.5
17	PanaboCity_LowerPanaga	364	5	57.5	5	247.5	20	28	1	620	653	415
18	PanaboCity_Mabunao	456.5	6.5	72.5	6	311	25	35.5	1	779	820.5	521
19	PanaboCity_Maduao	744	11	117.5	10	506.5	40.5	58	1	1268	1336.5	849
20	PanaboCity_Malativas	574	8	90.5	8	390.5	31	44.5	1	977.5	1030.5	654.5
21	PanaboCity_Manay	1292	18	204	18	879	70.5	100.5	2	2201.5	2320	1473.5
22	PanaboCity_Nanyo	919	13	145	13	625.5	50	71.5	1	1567	1651.5	1048.5
23	PanaboCity_NewMalaga	438.5	6	69.5	6	298.5	24	34	1	747.5	788	500
24	PanaboCity_NewMalitbog	783	11	123.5	11	533	42.5	61	1	1334.5	1406.5	893
25	PanaboCity_NewPandan	1586	22.5	250.5	22	1079	86.5	123.5	2	2703	2848	1809
26	PanaboCity_NewVisayas	3959	56	625.5	54.5	2693.5	216	308	6	6747	7110	4515.5
27	PanaboCity_Quezon	1111	16	175.5	15	756	60.5	86.5	2	1893.5	1995.5	1267
28	PanaboCity_Salvacion	2275.5	32	359.5	31	1548	124	177	3	3878	4086	2595
29	PanaboCity_SanFrancisco	3066.5	43.5	484.5	42	2086.5	167	238.5	4	5226	5507.5	3497.5
30	PanaboCity_SanNicolas	495	7	78.5	7	337	27	38.5	1	843.5	889	564.5
31	PanaboCity_SanPedro	114.5	2	18	2	78	6	9	0	195.5	206	131
32	PanaboCity_SanRoque	3453	49	546	47.5	2349	188	268.5	5	5885	6201.5	3938
33	PanaboCity_SanVicente	291.5	4	46	4	198.5	16	23	0	497.5	524	332.5
34	PanaboCity_SantaCruz	1035.5	15	163.5	14	704.5	56.5	80.5	2	1764.5	1859.5	1180.5
35	PanaboCity_SantoNino	811.5	11.5	128.5	11	552	44	63	1	1383	1457.5	925.5
36	PanaboCity_Sindaton	2156	30.5	340.5	29.5	1467	117.5	168	3	3674	3871.5	2459
37	PanaboCity_SouthernDavao	393	6	62	5	267.5	21.5	30.5	1	669.5	705	447.5
38	PanaboCity_Tagpore	398	6	62.5	5.5	270.5	22	31	1	677.5	714.5	453.5
39	PanaboCity_Tibungol	379.5	5	60	5	258.5	21	29.5	1	647	681.5	433
40	PanaboCity_UpperLicanan	232	3	36.5	3	158	13	18	0	395.5	416.5	264.5
41	PanaboCity_Waterfall	1002.5	14	158	14	681.5	54.5	78	1	1708	1799.5	1142.5
42	SamalCity_Adecor1	490	7	77.5	7	333.5	26.5	38	1	771.5	813.5	516.5
43	SamalCity_Adecor2	490	7	77.5	7	333.5	26.5	38	1	771.5	813.5	516.5
44	SamalCity_Anonang	648.5	9	102.5	9	441.5	35.5	50.5	1	1021	1076	683.5
45	SamalCity_Aumbay	524.5	7.5	83	7	357	28.5	40.5	1	826	870.5	553
46	SamalCity_Aundanao	335	5	53	5	228	18	26	0	527.5	556	353
47	SamalCity_Balet1	751	11	119	10	511	41	58.5	1	1183.5	1247	792
48	SamalCity_Balet2	751	11	119	10	511	41	58.5	1	1183.5	1247	792
49	SamalCity_Balet3	751	11	119	10	511	41	58.5	1	1183.5	1247	792
50	SamalCity_Bandera	454.5	6.5	71.5	6	309.5	25	35.5	1	716	754.5	479
51	SamalCity_Caliclic	620	9	98	8.5	421.5	34	48.5	1	976	1028.5	653.5
52	SamalCity_Camudmud	667	9.5	105.5	9	453.5	36.5	51.5	1	1050.5	1106.5	703
53	SamalCity_Catagman	337.5	5	53.5	5	229.5	18.5	26	0	531	560	355.5
54	SamalCity_Cawag	672.5	9.5	106	9	457.5	36.5	52.5	1	1058.5	1116	708.5
55	SamalCity_Cogon2	763	11	120.5	10.5	519	41.5	59.5	1	1201.5	1266	804
56	SamalCity_Cogon1	531	7.5	84	7	361	29	41.5	1	836.5	881.5	560
57	SamalCity_Dadatan	369.5	5	58.5	5	251	20	29	1	582	613	389.5
58	SamalCity_DelMonte	498	7	78.5	7	339	27	38.5	1	784	826.5	525

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59	SamalCity_Guilon	404	6	63.5	6	275	22	31.5	1	636	670	425.5
60	SamalCity_Kanaan	377	5	59.5	5	257	20.5	29.5	1	594	626	397.5
61	SamalCity_Kinawitnon	513	7	81	7	349	28	40	1	808.5	851.5	541
62	SamalCity_Libertad	619.5	9	98	8.5	421.5	33.5	48.5	1	976	1028	653
63	SamalCity_Libuak	383	5	60.5	5	260.5	21	30	1	603	635.5	403.5
64	SamalCity_Licup	231	3	36.5	3	157.5	12.5	18	0	364.5	384	244
65	SamalCity_Limao	649.5	9	102.5	9	441.5	35.5	50.5	1	1023	1078	684.5
66	SamalCity_Linosutan	222	3	35	3	151	12	17	0	349.5	368.5	234
67	SamalCity_MambagoA	476.5	7	75.5	7	324.5	26	37	1	750.5	791	502.5
68	SamalCity_MambagoB	688.5	10	109	9.5	468.5	37.5	53.5	1	1084.5	1143	726
69	SamalCity_Miranda	1850	26	292.5	25.5	1259	101	144	3	2913.5	3070	1950
70	SamalCity_Moncado	973.5	14	154	13.5	662.5	53	75.5	1	1533.5	1616	1026.5
71	SamalCity_Pangubatan	360	5	56.5	5	245	19.5	28	1	567.5	597.5	379.5
72	SamalCity_Penaplata	1585.5	22.5	251	22	1078.5	86.5	123	2	2497	2632	1671.5
73	SamalCity_Poblacion	1036	15	163.5	14	704.5	56.5	80.5	1.5	1631.5	1719	1092
74	SamalCity_SanAgustin	468	7	74	6	318.5	25.5	36.5	1	737	776.5	493
75	SamalCity_SanAntonio	545.5	8	86.5	7.5	371	29.5	42.5	1	859.5	905.5	575
76	SamalCity_SanIsidro1	585.5	8	92.5	8	398	32	45.5	1	921.5	971	617
77	SamalCity_SanIsidro2	404.5	6	63.5	6	275	22	31.5	1	637	672	426.5
78	SamalCity_SanJose	456.5	6.5	72.5	6	310.5	25	35.5	1	718.5	757.5	481
79	SamalCity_SanMiguel	427.5	6	67.5	6	291	23	33.5	1	673.5	709.5	451
80	SamalCity_SanRemigio	568.5	8	90	8	387	31	44.5	1	895.5	944	600
81	SamalCity_SantaCruz	992	14	156.5	14	675	54	77.5	1	1562	1646.5	1045.5
82	SamalCity_SantoNino	405	6	64.5	6	276	22	31.5	1	638	672	427
83	SamalCity_Sion	179.5	3	28.5	2	122	10	14	0	282.5	298	189
84	SamalCity_Tagbaobo	566.5	8	89.5	8	386	31	44	1	892.5	940.5	597
85	SamalCity_Tagbay	366	5	57.5	5	249	20	28.5	1	576	607	385.5
86	SamalCity_TagbitanAg	567.5	8	89.5	8	386	31	44.5	1	894	942	598
87	SamalCity_Tagdaliao	199	3	31.5	3	135	11	15.5	0	313.5	330	210
88	SamalCity_Tagpopongan	366.5	5	57.5	5	249	20	28.5	1	577	608	386.5
89	SamalCity_Tambo1	1137	16	179.5	16	773.5	61.5	88.5	2	1790.5	1886.5	1198
90	SamalCity_Tambo2	1137	16	179.5	16	773.5	61.5	88.5	2	1790.5	1886.5	1198
91	SamalCity_Toril	813.5	11.5	129	11	553.5	44.5	63.5	1	1281	1350	857.5
92	TagumCity_Apokon	7140.5	101.5	1128	98.5	4858	389.5	555.5	10	12544	13219	8395.5
93	TagumCity_Bincungan	1014.5	14	160	14	690.5	55.5	78.5	1	1782.5	1878.5	1193
94	TagumCity_Busaon	683.5	10	108	9	465	37	53	1	1200.5	1265.5	803.5
95	TagumCity_Canocotan	1953.5	28	309	27	1328.5	106.5	152	3	3431.5	3616	2296.5
96	TagumCity_Cuambogan	2547.5	36	402.5	35	1733	139	198	4	4475.5	4716.5	2995.5
97	TagumCity_LaFilipina	3694.5	52.5	583.5	51	2514	201.5	287	5	6491	6840	4344
98	TagumCity_Liboganon	547.5	8	86.5	7.5	372.5	30	42.5	1	961	1013	643
99	TagumCity_Madaum1	2573.5	36.5	406.5	35.5	1751	140	200	4	4521.5	4764.5	3026
100	TagumCity_Madaum2	2573.5	36.5	406.5	35.5	1751	140	200	4	4521.5	4764.5	3026
101	TagumCity_Magdum	2452.5	35	387.5	34	1668.5	133.5	191	4	4309	4540	2883.5
102	TagumCity_Mankilam	9353.5	133	1477.5	128.5	6363.5	509.5	727.5	14	16432.5	17317	10998
103	TagumCity_NewBalamban	351.5	5	55.5	5	239.5	19	27.5	1	617.5	650.5	413.5
104	TagumCity_NuevaFuerza	469	7	74.5	6	319	25.5	36.5	1	823	867.5	551
105	TagumCity_Pagsabangan	1260	18	199	17	857.5	68.5	98	2	2214	2333.5	1481.5
106	TagumCity_Pandapan	572.5	8	90.5	8	389.5	31	44.5	1	1006	1060.5	673.5
107	TagumCity_MagugpoPoblacion	760	11	120	10.5	517	41.5	59	1	1334.5	1406.5	893
108	TagumCity_SanAgustin	267.5	4	42.5	4	182	14.5	21	0	470.5	495.5	314.5
109	TagumCity_SanIsidro	1151.5	16	182	16	783	62.5	89.5	2	2022.5	2131.5	1353.5
110	TagumCity_SanMiguel	4157.5	59	657	57.5	2828	226.5	323	6	7303	7696.5	4888
111	TagumCity_VisayanVillage	9673.5	137	1528.5	133	6581.5	527	752.5	14	16995	17909.5	11374.5
112	TagumCity_MagugpoEast	3463	49	547.5	47.5	2356	189	269.5	5	6084.5	6412	4072
113	TagumCity_MagugpoNorth	2243	32	354.5	31	1526	122	174.5	3	3941	4152.5	2637.5
114	TagumCity_MagugpoSouth	2600.5	37	410.5	36	1769	142	202.5	4	4568.5	4814.5	3057.5
115	TagumCity_MagugpoWest	3352.5	47.5	529.5	46	2280.5	183	260.5	5	5890	6206.5	3942

1	location	Labor,Underemployed	Labor,Unemployed	Poverty,poverty incidence by employed	Poverty,poverty incidence by household	Poverty,poverty incidence by population	Poverty,poverty incidence by unemployed	Children Population	Teenage Population	Adult Population	Retiree Population
2	PanaboCity_AOFloirendo	328	106	325.5	192	1096	19.5	1075.5	977	2577	351
3	PanaboCity_Buenavista	392	127	389	230	1310	23	1286.5	1167	3080	419.5
4	PanaboCity_Cacao	54	17.5	54	32	181	3	177.5	162	425.5	58
5	PanaboCity_Cagangohan	81	26	80.5	47.5	270.5	5	265.5	241	636.5	87
6	PanaboCity_Consolacion	932.5	302	926	546.5	3114.5	54.5	3058.5	2775.5	7324	999
7	PanaboCity_Dapco	118	38	117.5	69.5	395	7	388	351.5	927.5	127.5
8	PanaboCity_DatuAbdulDadia	275.5	89.5	273.5	161.5	920	16.5	903.5	819.5	2162.5	295
9	PanaboCity_Gredu	1120	362.5	1111.5	656.5	3740	66	3672.5	3333.5	8795	1200
10	PanaboCity_JPLaurel	444.5	144	441	260.5	1483	26	1456.5	1322	3487.5	475.5
11	PanaboCity_Kasilak	188.5	61	187.5	110.5	630.5	11	618.5	562	1481.5	202.5
12	PanaboCity_Katipunan	124.5	40	123.5	72.5	415	7	407	370	976	133
13	PanaboCity_Katualan	50.5	16.5	50	29.5	168	3	165.5	150	395	54
14	PanaboCity_Kauswagan	96	31	95.5	56.5	321	5.5	315	286	754.5	103
15	PanaboCity_Kiotoy	101.5	33	101	59.5	339	6	333.5	302.5	798	108
16	PanaboCity_LittlePanay	164.5	53.5	163.5	96.5	550	9.5	540	490	1293.5	176.5
17	PanaboCity_LowerPanaga	103	33	102.5	60.5	344	6	338	306.5	809	110.5
18	PanaboCity_Mabunao	129.5	42	128.5	75.5	432.5	7.5	424.5	386	1016.5	138.5
19	PanaboCity_Maduao	211	68	209	123.5	704	12.5	691	627.5	1654.5	225
20	PanaboCity_Malativas	162.5	52.5	161.5	95.5	543	9.5	533.5	484	1277	173.5
21	PanaboCity_Manay	366	118.5	363.5	214.5	1222.5	21.5	1200.5	1089.5	2874.5	392
22	PanaboCity_Nanyo	260.5	84.5	258.5	152.5	869.5	15.5	854.5	775	2045	279
23	PanaboCity_NewMalaga	124.5	40	123	72.5	415	7	407	370	974.5	132
24	PanaboCity_NewMalitbog	222	72	220	130	741	13	727	660	1741.5	237.5
25	PanaboCity_NewPandan	449	145.5	446	263.5	1500	26.5	1473.5	1337	3528.5	481
26	PanaboCity_NewVisayas	1121	363.5	1113.5	657.5	3745.5	66	3677	3337.5	8807	1201.5
27	PanaboCity_Quezon	314.5	102	312.5	184	1051	18.5	1032.5	936.5	2470.5	337
28	PanaboCity_Salvacion	644.5	209	640	378	2152.5	38	2114	1918	5061.5	691
29	PanaboCity_SanFrancisco	868.5	281	862.5	509	2901	50.5	2849	2585.5	6821.5	930.5
30	PanaboCity_SanNicolas	140	45.5	139	82.5	468.5	8	459.5	417	1101	150.5
31	PanaboCity_SanPedro	32.5	10.5	32.5	19	108.5	2	106.5	97	255.5	35
32	PanaboCity_SanRoque	978	316.5	971	573	3266.5	57.5	3208	2911.5	7681	1048
33	PanaboCity_SanVicente	82.5	27	82	48.5	276.5	5	271	246.5	648.5	88.5
34	PanaboCity_SantaCruz	293.5	95	291	172	979.5	17.5	962	873	2302.5	314.5
35	PanaboCity_SantoNino	229.5	74.5	228	134.5	768	13.5	754	684.5	1806	246
36	PanaboCity_Sindaton	610.5	197.5	606	358	2039.5	36	2003	1817.5	4796.5	654
37	PanaboCity_SouthernDavao	111.5	36	110.5	65.5	371	6.5	365	331.5	873.5	118.5
38	PanaboCity_Tagpore	112.5	36.5	111.5	66	376	6.5	369	335.5	884.5	120.5
39	PanaboCity_Tibungol	107.5	35	106.5	63	359	6	352.5	320	843	115.5
40	PanaboCity_UpperLicanan	66	21.5	65.5	38.5	219.5	4	216	195	517	70
41	PanaboCity_Waterfall	283.5	92	281.5	166	948	16.5	931	845	2230	304
42	SamalCity_Adecor1	128.5	41.5	127.5	81.5	431.5	7.5	427.5	384	963	184.5
43	SamalCity_Adecor2	128.5	41.5	127.5	81.5	431.5	7.5	427.5	384	963	184.5
44	SamalCity_Anonang	169.5	55	168.5	107.5	570.5	10	566.5	508	1274	244.5
45	SamalCity_Aumbay	137.5	44.5	136.5	87	461.5	8	457.5	411.5	1031.5	198
46	SamalCity_Aundanao	88	28	87	55.5	294.5	5	292.5	262.5	658.5	126
47	SamalCity_Balet1	197	64	195	125	661	11.5	656	589	1476	283.5
48	SamalCity_Balet2	197	64	195	125	661	11.5	656	589	1476	283.5
49	SamalCity_Balet3	197	64	195	125	661	11.5	656	589	1476	283.5
50	SamalCity_Bandera	119	38.5	118.5	75.5	400	7	396.5	357	894	171.5
51	SamalCity_Caliclic	162	52.5	161	103	545.5	9.5	540.5	485.5	1218.5	233
52	SamalCity_Camudmud	174.5	56.5	173.5	111	586.5	10.5	582	523	1311	252
53	SamalCity_Catagman	88	28.5	87.5	56	297	5	294.5	264.5	663.5	127
54	SamalCity_Cawag	176	57	174.5	111.5	591.5	10.5	587	527	1321	253.5
55	SamalCity_Cogon2	199.5	65	198	127	671.5	11.5	666	598	1499	287.5
56	SamalCity_Cogon1	139	45	138	88	467.5	8	463	416	1043.5	200.5
57	SamalCity_Dadatan	97	31	96	61.5	325.5	5.5	322.5	290	726.5	139.5
58	SamalCity_DelMonte	130	42.5	129.5	82.5	438.5	7.5	435	390.5	978.5	188

1	location	Labor,Underemployed	Labor,Unemployed	Poverty,poverty incidence by employed	Poverty,poverty incidence by household	Poverty,poverty incidence by population	Poverty,poverty incidence by unemployed	Children Population	Teenage Population	Adult Population	Retiree Population
59	SamalCity_Guilon	105.5	34	105	67.5	355.5	6	352.5	316.5	794.5	153
60	SamalCity_Kanaan	99	32	98	62.5	331.5	6	329	296	740.5	142.5
61	SamalCity_Kinawitnon	134.5	43.5	133.5	85.5	451.5	8	447.5	403	1009	193.5
62	SamalCity_Libertad	162	52.5	161	103	545	9.5	540.5	485.5	1217.5	233
63	SamalCity_Libuak	100	32	99.5	63.5	337	6	334	300.5	752.5	144.5
64	SamalCity_Licup	60.5	19.5	60	38.5	203.5	3.5	201.5	181	454.5	87
65	SamalCity_Limao	169.5	55	168.5	108	571.5	10	567	510	1277.5	245
66	SamalCity_Linosutan	58	18.5	57.5	37	195.5	3.5	194	174	435.5	83.5
67	SamalCity_MambagoA	124.5	40.5	123.5	79.5	419.5	7.5	416	374	936.5	180
68	SamalCity_MambagoB	180.5	58.5	179	114	606	10.5	601	540	1353.5	260.5
69	SamalCity_Miranda	484	157	481	307.5	1628	28	1614	1450.5	3636.5	698
70	SamalCity_Moncado	255	82.5	253	161.5	857	14.5	849.5	764	1914	367.5
71	SamalCity_Pangubatan	94.5	30.5	94	59.5	316.5	5.5	314.5	282.5	708.5	136
72	SamalCity_Penaplata	415	134.5	412	263	1395	24.5	1384	1243.5	3117.5	599.5
73	SamalCity_Poblacion	271	88	269.5	172	911.5	15.5	903.5	812.5	2036	392
74	SamalCity_SanAgustin	122.5	39.5	121.5	77.5	411.5	7	408.5	367	919	176
75	SamalCity_SanAntonio	143	46.5	142	90.5	480	8.5	477	428	1072.5	206.5
76	SamalCity_SanIsidro1	153	49.5	152	97	515	9	511	459	1151	220.5
77	SamalCity_SanIsidro2	106	34	105	67.5	356	6	353.5	317.5	795.5	153
78	SamalCity_SanJose	119	38.5	118.5	75.5	401.5	7	398	357.5	897	172.5
79	SamalCity_SanMiguel	112	36	111	71	376	6.5	373	335	839	161.5
80	SamalCity_SanRemigio	148.5	48.5	148	94.5	500.5	8.5	497	445.5	1118	215.5
81	SamalCity_SantaCruz	259.5	84	257.5	164.5	873	15.5	865.5	778	1950	375
82	SamalCity_SantoNino	106	34	105	67.5	356.5	6	354	317.5	797.5	153
83	SamalCity_Sion	47	15.5	47	30	158	3	157	141	353.5	67
84	SamalCity_Tagbaobo	148.5	48.5	147	94	499	8.5	495	444.5	1114.5	213.5
85	SamalCity_Tagbay	95.5	31	95	60.5	322	5.5	319.5	287.5	720	138.5
86	SamalCity_TagbitanAg	148.5	48.5	148	94.5	500	8.5	495.5	445.5	1116	214
87	SamalCity_Tagdaliao	52	16.5	52	33	175	3	174	156	392	75
88	SamalCity_Tagpopongan	96	31	95	60.5	322.5	5.5	319.5	287.5	721.5	138.5
89	SamalCity_Tambo1	297.5	96	295	188.5	1000	17.5	992	892	2234	429
90	SamalCity_Tambo2	297.5	96	295	188.5	1000	17.5	992	892	2234	429
91	SamalCity_Toril	212.5	69	211.5	135	716	12.5	710.5	638	1599	307.5
92	TagumCity_Apokon	2084.5	675	2069.5	1185.5	6755	122.5	6227	5961.5	16333	2182.5
93	TagumCity_Bincungan	296.5	96	294.5	168.5	960	17.5	884.5	847	2321.5	310.5
94	TagumCity_Busaon	199.5	65	198	113.5	646.5	11.5	596	571	1563.5	209.5
95	TagumCity_Canocotan	570	184.5	566.5	324	1847.5	33	1703.5	1630.5	4467.5	597
96	TagumCity_Cuambogan	744	241	738.5	423	2410	43.5	2222	2127.5	5827	778.5
97	TagumCity_LaFilipina	1079	349.5	1071	613	3495	63	3221.5	3084.5	8450.5	1129
98	TagumCity_Liboganon	160	51.5	158.5	90.5	517.5	9.5	476.5	457	1252.5	167
99	TagumCity_Madaum1	751.5	243.5	746.5	427.5	2434.5	44	2244	2148.5	5888	786.5
100	TagumCity_Madaum2	751.5	243.5	746.5	427.5	2434.5	44	2244	2148.5	5888	786.5
101	TagumCity_Magdum	716	232	711	407.5	2320	42	2139	2047.5	5609.5	750.5
102	TagumCity_Mankilam	2731	884.5	2711.5	1553	8848.5	160	8156.5	7809	21396.5	2859
103	TagumCity_NewBalamban	102.5	33	102	58.5	332.5	6	306.5	294	804.5	107.5
104	TagumCity_NuevaFuerza	137	44.5	136	77.5	443	8	408.5	391.5	1072.5	143.5
105	TagumCity_Pagsabangan	368	119.5	365	209.5	1192.5	21.5	1099.5	1052	2883.5	385.5
106	TagumCity_Pandapan	167.5	54.5	166	95	541.5	10	499.5	478	1310.5	175
107	TagumCity_MagugpoPoblacion	221.5	72	220	126	718.5	13	662	635	1738	232
108	TagumCity_SanAgustin	78	25.5	77.5	44.5	253.5	4.5	234	223.5	612.5	81.5
109	TagumCity_SanIsidro	336	109	333.5	191	1089	19.5	1004.5	961.5	2634	352
110	TagumCity_SanMiguel	1213.5	393	1205	690	3933	71	3625	3471	9509.5	1270
111	TagumCity_VisayanVillage	2824.5	914.5	2804	1606	9151.5	166	8436	8076.5	22129.5	2957
112	TagumCity_MagugpoEast	1011	327.5	1004	575	3276.5	59	3020.5	2892	7923.5	1058.5
113	TagumCity_MagugpoNorth	655	212	650.5	372.5	2122.5	38.5	1955.5	1873	5131	685
114	TagumCity_MagugpoSouth	759.5	245.5	753.5	431.5	2460	44.5	2267.5	2171	5948.5	794.5
115	TagumCity_MagugpoWest	979	316.5	971.5	556.5	3171.5	57.5	2923.5	2798.5	7668	1025

1	location	Female Children Population	Female Teenage Population	Female Adult Population	Female Retiree Population	Male Children Population	Male Teenage Population	Male Adult Population	Male Retiree Population
2	PanaboCity_AOFloirendo	525.5	483.5	1260.5	184.5	551	493.5	1317.5	167
3	PanaboCity_Buenavista	628	578	1504.5	220.5	658	590	1576	199
4	PanaboCity_Cacao	87	80	208	31	90.5	81.5	217	27
5	PanaboCity_Cagangohan	129.5	119.5	311.5	46	136	122	325	42
6	PanaboCity_Consolacion	1493	1373.5	3580.5	525.5	1565	1403	3744.5	473.5
7	PanaboCity_Dapco	189	175	453.5	67	198	178	474.5	60
8	PanaboCity_DatuAbdulDadia	441	405.5	1056	155.5	462	414	1105.5	140
9	PanaboCity_Gredu	1793	1649	4298	631.5	1880	1684.5	4496	569
10	PanaboCity_JPLaurel	711	654	1703.5	250	745.5	668	1783	225.5
11	PanaboCity_Kasilak	302	277.5	723.5	106.5	316.5	284	758.5	96
12	PanaboCity_Katipunan	199	183	477	70.5	208	187	499.5	63
13	PanaboCity_Katualan	80.5	74	193	29	85	76	203	26
14	PanaboCity_Kauswagan	154	141.5	369	54	161.5	144.5	386	48.5
15	PanaboCity_Kiotoy	162	149.5	389.5	58	170	153	408	51
16	PanaboCity_LittlePanay	264	242.5	632.5	92	276	247.5	662	83.5
17	PanaboCity_LowerPanaga	164.5	152	394.5	58.5	174	155	414	51.5
18	PanaboCity_Mabunao	207	191	497.5	72	217	195	520	66
19	PanaboCity_Maduao	337.5	310.5	809	119	353.5	317	846.5	107
20	PanaboCity_Malativas	260	239.5	623	91.5	273.5	244.5	652.5	82
21	PanaboCity_Manay	586	539	1404.5	206	613.5	550	1469	185.5
22	PanaboCity_Nanyo	417	383	1000.5	146.5	437	391.5	1044.5	132
23	PanaboCity_NewMalaga	199	183	477	70.5	208	187	499.5	63
24	PanaboCity_NewMalitbog	355	326.5	852	125	372	333	890.5	112.5
25	PanaboCity_NewPandan	719	661.5	1724.5	253.5	753	675.5	1803	229
26	PanaboCity_NewVisayas	1795.5	1651	4304	632	1882	1686.5	4502.5	569.5
27	PanaboCity_Quezon	503.5	463.5	1208	178	528.5	473.5	1262.5	160.5
28	PanaboCity_Salvacion	1032	949	2474.5	363	1082	969	2588	328
29	PanaboCity_SanFrancisco	1390.5	1279.5	3333.5	489.5	1458	1306	3487.5	441.5
30	PanaboCity_SanNicolas	225	206	539	79	236	211	563.5	71
31	PanaboCity_SanPedro	51.5	48	124	19	55	49	131	15
32	PanaboCity_SanRoque	1566.5	1440.5	3754.5	551	1641.5	1471	3927.5	496.5
33	PanaboCity_SanVicente	132	122	316.5	46.5	138.5	124	332	42.5
34	PanaboCity_SantaCruz	469.5	432	1125.5	165.5	492	441	1177	149.5
35	PanaboCity_SantoNino	368	338	883	130.5	386	346	922	117.5
36	PanaboCity_Sindaton	978	899	2344.5	344.5	1024.5	918.5	2453	310
37	PanaboCity_SouthernDavao	178.5	163.5	427.5	62.5	186	167	446.5	57
38	PanaboCity_Tagpore	180.5	165.5	433	64	189	169.5	452.5	57
39	PanaboCity_Tibungol	172	158.5	412.5	60	180	161.5	432	56
40	PanaboCity_UpperLicanan	105	97	252	37.5	110	99	264.5	34
41	PanaboCity_Waterfall	454	418	1090.5	159.5	476.5	427	1138.5	144
42	SamalCity_Adecor1	208	182	463	95	219.5	202	499.5	89
43	SamalCity_Adecor2	208	182	463	95	219.5	202	499.5	89
44	SamalCity_Anonang	275	241	613.5	127.5	291	267	661.5	118
45	SamalCity_Aumbay	222.5	195	497.5	102.5	235	216	535	96
46	SamalCity_Aundanao	142.5	124	316.5	65.5	151	138	342	61.5
47	SamalCity_Balet1	318.5	279.5	710.5	146.5	337.5	310	767	137.5
48	SamalCity_Balet2	318.5	279.5	710.5	146.5	337.5	310	767	137.5
49	SamalCity_Balet3	318.5	279.5	710.5	146.5	337.5	310	767	137.5
50	SamalCity_Bandera	193	169	429	88	204	187.5	464.5	83
51	SamalCity_Caliclic	262.5	231	586	121	278	256	633.5	112.5
52	SamalCity_Camudmud	282	248	630	129.5	299	275	681	121.5
53	SamalCity_Catagman	143	126	319	65.5	151	139	344	62
54	SamalCity_Cawag	285	250	635.5	131	301.5	277	685	122.5
55	SamalCity_Cogon2	323.5	284	720.5	148.5	342	315	778.5	139.5
56	SamalCity_Cogon1	225.5	197.5	501	103.5	238.5	219	542	96.5
57	SamalCity_Dadatan	157	137	348.5	71.5	165	152.5	376	67.5
58	SamalCity_DelMonte	211.5	185.5	470	96.5	223.5	205	508	90.5

1	location	Female Children Population	Female Teenage Population	Female Adult Population	Female Retiree Population	Male Children Population	Male Teenage Population	Male Adult Population	Male Retiree Population
59	SamalCity_Guilon	171.5	150.5	383	78.5	181.5	166.5	412	73
60	SamalCity_Kanaan	159.5	140.5	355.5	74	169.5	155.5	385.5	68.5
61	SamalCity_Kinawitnon	217.5	190.5	484.5	100.5	230	211.5	524.5	94
62	SamalCity_Libertad	262.5	231	586	121	278	256	632.5	112.5
63	SamalCity_Libuak	162.5	143	361	75	172	158	391.5	69.5
64	SamalCity_Licup	98.5	86	218.5	45.5	104	95.5	235.5	42.5
65	SamalCity_Limao	275.5	241	614	127.5	291.5	268	662.5	118
66	SamalCity_Linosutan	94	82.5	209.5	43	99.5	92	227	41
67	SamalCity_MambagoA	202	177	451.5	93.5	214	196.5	487	87
68	SamalCity_MambagoB	292	256	651	134.5	309	284	703	125.5
69	SamalCity_Miranda	784.5	687.5	1749	360	830	762.5	1887	337
70	SamalCity_Moncado	412.5	362.5	920	189.5	437	401	993.5	177
71	SamalCity_Pangubatan	153	134	341.5	70	161.5	149	368.5	65.5
72	SamalCity_Penaplata	672.5	590	1499	310	711	654.5	1618	289
73	SamalCity_Poblacion	439.5	385.5	980	203	464	427	1057	188.5
74	SamalCity_SanAgustin	198.5	174.5	442.5	91.5	209.5	193	478	85.5
75	SamalCity_SanAntonio	231	203	515.5	106.5	245	225.5	557	98.5
76	SamalCity_SanIsidro1	248	218	553	114.5	262	241	598	106.5
77	SamalCity_SanIsidro2	171.5	151	383.5	78.5	182	167	413	73.5
78	SamalCity_SanJose	193.5	169.5	431.5	88.5	204.5	188	465.5	83.5
79	SamalCity_SanMiguel	181.5	159.5	405	83	192	176.5	435.5	78
80	SamalCity_SanRemigio	241	211.5	537.5	111	255	235	581	104.5
81	SamalCity_SantaCruz	421	369	937.5	194	444.5	409	1012	181
82	SamalCity_SantoNino	171.5	151	384	78.5	182	167	413	73.5
83	SamalCity_Sion	76	66.5	168.5	34.5	80.5	74	183.5	32.5
84	SamalCity_Tagbaobo	240	210.5	535.5	110.5	254	233.5	578	104
85	SamalCity_Tagbay	155	136	347.5	70.5	164	151	374	67
86	SamalCity_TagbitanAg	241	211.5	536	111	255	234	579.5	104.5
87	SamalCity_Tagdaliao	84	74	188.5	39.5	89.5	82	203.5	35.5
88	SamalCity_Tagpopongan	155	136	347.5	71	164.5	151	375	67
89	SamalCity_Tambo1	482.5	422.5	1074	221.5	510	468.5	1160	207.5
90	SamalCity_Tambo2	482.5	422.5	1074	221.5	510	468.5	1160	207.5
91	SamalCity_Toril	345.5	302.5	769.5	158.5	365	335	831	148
92	TagumCity_Apokon	3013	2967	8113	1172.5	3213	2995	8219.5	1009
93	TagumCity_Bincungan	428	421.5	1153	167	456.5	425.5	1167.5	144
94	TagumCity_Busaon	288.5	283.5	776	112.5	307	286.5	787	96.5
95	TagumCity_Canocotan	824.5	811.5	2220	321.5	879	819	2248	277
96	TagumCity_Cuambogan	1075.5	1058	2895	418	1146	1068	2932.5	361
97	TagumCity_LaFilipina	1559.5	1534.5	4197.5	606.5	1662	1549.5	4252.5	522.5
98	TagumCity_Liboganon	231	227.5	622	91	246	229.5	629	78
99	TagumCity_Madaum1	1086	1069.5	2925	423	1158	1079.5	2962.5	363.5
100	TagumCity_Madaum2	1086	1069.5	2925	423	1158	1079.5	2962.5	363.5
101	TagumCity_Magdum	1035	1018.5	2787.5	403	1103.5	1028.5	2822	347
102	TagumCity_Mankilam	3948	3886.5	10629	1536	4209	3923	10766.5	1322.5
103	TagumCity_NewBalamban	148.5	146	398.5	58.5	158.5	148	405	48
104	TagumCity_NuevaFuerza	197.5	195	533	76.5	211	197	539.5	67
105	TagumCity_Pagsabangan	532	524	1431.5	207.5	567	528.5	1451	178
106	TagumCity_Pandapan	242	238	650.5	94	257.5	240	659.5	81.5
107	TagumCity_MagugpoPoblacion	320.5	315	863	124.5	341.5	318.5	874.5	107
108	TagumCity_SanAgustin	113	111.5	303.5	44	121	112.5	308	38
109	TagumCity_SanIsidro	486.5	478	1308.5	189	518	483	1325	162.5
110	TagumCity_SanMiguel	1755	1727	4723.5	683.5	1870.5	1744	4784	588
111	TagumCity_VisayanVillage	4083	4019.5	10994	1588.5	4352.5	4057.5	11134	1368
112	TagumCity_MagugpoEast	1462	1439	3936.5	568.5	1558	1452	3986.5	490
113	TagumCity_MagugpoNorth	947.5	932	2550	369	1010	941	2581.5	317.5
114	TagumCity_MagugpoSouth	1097.5	1080.5	2955	427	1170.5	1091	2993	367.5
115	TagumCity_MagugpoWest	1415	1393	3810.5	550	1508	1406.5	3860	473.5

Appendix C. Crime Data

Shows first 50 crime instances with all 114 independent variable values.

	crime	barangay	city	Temp (deg celsius)	Feels Like (deg celsius)	Wind (km/h)	Cloud	Humidity	Precip (mm)	Pressure (mb)
1	Murder/Homicide	Magugpo Poblacion	Tagum City	23	25	8	18	89	0	1013
2	Physical Injuries	Magugpo Poblacion	Tagum City	23	25	8	18	89	0	1013
3	Murder/Homicide	Magugpo North	Tagum City	27	29	13	1	66	0	1013
4	Physical Injuries	Magugpo North	Tagum City	27	29	13	1	66	0	1013
5	Drug Related Incident (RA	New Visayas	Panabo City	39	51	9	9	52	0	1009
6	Theft	Mambago-A	Samal City	37	51	13	28	63	0.1	1008
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	37	46	6	10	47	0.1	1009
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	36	45	8	30	51	0.2	1008
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	29	28	1	38	80	0.5	1011
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	29	29	1	41	79	0.3	1011
11	Murder/Homicide	San Isidro	Tagum City	34	40	8	72	62	0.7	1010
12	Physical Injuries	Magugpo South	Tagum City	31	28	3	73	93	0.9	1011
13	Theft	Magugpo South	Tagum City	34	40	8	72	62	0.7	1010
14	Theft	Magugpo Poblacion	Tagum City	34	35	3	46	70	0.4	1011
15	Drug Related Incident (RA	Cagangohan	Panabo City	35	38	4	28	63	0	1010
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	36	47	7	54	58	0.3	1008
17	Carnapping (R.A. 6539)	Apokon	Tagum City	36	44	5	37	53	0.2	1008
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	34	40	3	52	69	0.4	1008
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	31	30	3	32	81	0.1	1009
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	32	35	1	18	75	0.5	1009
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	32	26	3	19	82	0	1008
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	31	30	1	77	82	0.5	1011
23	Theft	La Filipina	Tagum City	37	44	7	55	59	2.2	1009
24	Murder/Homicide	Madaum	Tagum City	33	30	4	36	81	0.8	1011
25	Theft	Kiotoy	Panabo City	35	39	5	0	63	0	1012
26	Robbery	Magugpo South	Tagum City	36	41	4	17	61	0	1012
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	34	37	9	29	68	0.2	1010
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	32	29	2	0	86	0	1012
29	Carnapping (R.A. 6539)	Apokon	Tagum City	36	44	9	45	55	0.5	1010
30	Physical Injuries	New Pandan (Pob.)	Panabo City	36	44	13	0	56	0	1010
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	32	25	2	11	88	0.3	1011
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	32	25	2	11	88	0.3	1011
33	Murder/Homicide	New Malitbog	Panabo City	34	29	3	0	79	0	1012
34	Robbery	La Filipina	Tagum City	32	25	2	11	88	0.3	1011
35	Physical Injuries	New Malitbog	Panabo City	38	46	5	0	46	0	1010
36	Robbery	Apokon	Tagum City	32	25	2	11	88	0.3	1011
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	35	29	2	0	80	0	1012
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	38	46	4	0	46	0	1010
39	Drug Related Incident (RA	Licup	Samal City	32	31	10	15	78	1.2	1011
40	Theft	San Pedro	Panabo City	32	32	8	21	81	0.6	1011
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	34	29	1	0	78	0	1011
42	Carnapping (R.A. 6539)	Apokon	Tagum City	34	29	1	0	78	0	1011
43	Robbery	Magugpo West	Tagum City	34	29	3	0	83	0	1011
44	Physical Injuries	Magugpo East	Tagum City	36	38	5	0	60	0	1011
45	Theft	Santo Niv±o (Pob.)	Panabo City	36	43	12	0	50	0	1009
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	32	34	7	0	78	0	1011
47	Physical Injuries	Magugpo Poblacion	Tagum City	32	32	4	17	79	0.5	1011
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	34	38	9	16	62	0.4	1010
49	Robbery	Magugpo East	Tagum City	32	32	4	17	79	0.5	1011
50	Murder/Homicide	Licup	Samal City	35	39	4	0	62	0	1011

	crime	barangay	city	Bank	Bar	Beach	Bridge	Cemetery	Church	Clinic
1	Murder/Homicide	Magugpo Poblacion	Tagum City	1	1	0	0	0	1	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	1	0	0	0	0	0	0
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	0	0	1	0
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	0	0	1	0
5	Drug Related Incident (RA	New Visayas	Panabo City	0	0	0	0	0	0	0
6	Theft	Mambago-A	Samal City	0	0	0	0	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1	1	0	0	0	1	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	0	0	0	1	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	0	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	1	0	0	0	1	0
13	Theft	Magugpo South	Tagum City	0	1	0	0	0	1	0
14	Theft	Magugpo Poblacion	Tagum City	1	1	0	0	0	0	0
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	1	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	1	0	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	0	0	0	0	0	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	0	0	0	0	0	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	0	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	0	0	0	0	0
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	0	0	0	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	0	0	0	0	1	0
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	0	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	0	0	0	0	0
34	Robbery	La Filipina	Tagum City	0	0	0	0	1	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	0	0	0	0	0
36	Robbery	Apokon	Tagum City	0	0	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	0	0	0	0	0	0
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	0	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	0	0	0	0	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	0	0	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	0	0	0	0
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	0	0	0	0	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	0	0	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	1	0	0	0	0	0	0
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	0	0	0
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	1	0

	crime	barangay	city	Commercial Building	Community Center	Convenience Store	Fire Station	Gas Station	Government Office	Greenfield
1	Murder/Homicide	Magugpo Poblacion	Tagum City	1	0	1	0	0	0	1
2	Physical Injuries	Magugpo Poblacion	Tagum City	1	1	0	0	1	0	1
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	0	1	0	1
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	0	1	0	1
5	Drug Related Incident (RA	New Visayas	Panabo City	1	0	0	0	0	0	0
6	Theft	Mambago-A	Samal City	1	0	0	0	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1	1	1	0	0	0	1
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	1	0	0	0	0	0	1
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	1	0	0	0	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	0	0	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	1	0	0	0	1	0	1
13	Theft	Magugpo South	Tagum City	1	0	0	0	1	0	1
14	Theft	Magugpo Poblacion	Tagum City	1	1	1	0	1	0	1
15	Drug Related Incident (RA	Cagangohan	Panabo City	1	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	0	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	0	0	1	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	0	0	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	1	0	0	0	1	0	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	1	0	0	0	0	0	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	0	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	1	0	0	0	0	0	0
25	Theft	Kiotoy	Panabo City	1	0	0	0	0	0	1
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1	0	0	0	0	1	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	1	1	1	1	0	1	1
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	0	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	1	0	0	0	0	0	1
34	Robbery	La Filipina	Tagum City	0	0	0	0	0	0	0
35	Physical Injuries	New Malitbog	Panabo City	1	0	0	0	0	0	0
36	Robbery	Apokon	Tagum City	0	0	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	1	0	0	1	1	1
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	1	0	0	0	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	1	0	0	0	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	0	0	0	0	0
43	Robbery	Magugpo West	Tagum City	1	0	0	0	0	0	0
44	Physical Injuries	Magugpo East	Tagum City	1	0	0	0	0	0	0
45	Theft	Santo Niv±o (Pob.)	Panabo City	1	0	0	0	1	0	1
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	1	0	0	0	0	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	1	1	0	0	1	0	1
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	0	0	0
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	1	0

	crime	barangay	city	Highway	Highway Pedestrian	Highway Primary	Highway Residential	Highway Secondary	Highway Tertiary
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	1	0	1	0	1
2	Physical Injuries	Magugpo Poblacion	Tagum City	1	1	0	1	0	1
3	Murder/Homicide	Magugpo North	Tagum City	1	1	0	1	0	1
4	Physical Injuries	Magugpo North	Tagum City	1	1	0	1	1	1
5	Drug Related Incident (RA	New Visayas	Panabo City	1	0	0	1	0	1
6	Theft	Mambago-A	Samal City	0	0	0	0	1	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	1	0	1
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	0	0	1	0	1
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	1	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	1	0	1
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	1	0	1
13	Theft	Magugpo South	Tagum City	0	0	0	1	0	1
14	Theft	Magugpo Poblacion	Tagum City	0	0	0	1	0	1
15	Drug Related Incident (RA	Cagangohan	Panabo City	1	0	0	1	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	1	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1	1	1	1	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	1	1	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	1	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	1	0	0	1	0	1
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	1	1	0	1	1	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	1	1	0	1
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	0	0	1	0	1
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	0	0	1	0	1
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	1	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	1	1	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	1	1	0	1	1	1
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	1	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	1	0	1	1	0	0
34	Robbery	La Filipina	Tagum City	0	1	0	1	0	0
35	Physical Injuries	New Malitbog	Panabo City	1	0	0	1	0	0
36	Robbery	Apokon	Tagum City	1	0	0	1	0	1
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	1	1	1	0	1
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	1	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	0	0	0	0	0	1
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	1	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	1	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	1	1	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	1	0	1
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	1	0	1	0	1
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	1	1	0	1	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	1	1	1	1	1	1
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	1	0	0	1	1	0
49	Robbery	Magugpo East	Tagum City	0	0	0	1	0	1
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	1

	crime	barangay	city	Hospital	Hotel	Industrial Building	Mall	Marketplace	Park	Parking Area
1	Murder/Homicide	Magugpo Poblacion	Tagum City	1	0	0	0	1	1	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	1	0	0	1	1	1	0
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	0	0	0	0
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	0	0	0	0
5	Drug Related Incident (RA	New Visayas	Panabo City	0	0	0	0	0	0	0
6	Theft	Mambago-A	Samal City	0	0	0	0	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1	1	0	0	1	1	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	0	0	0	0	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	0	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	1	0	0	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	0	0	0	0
13	Theft	Magugpo South	Tagum City	0	0	0	0	0	0	0
14	Theft	Magugpo Poblacion	Tagum City	0	1	0	0	1	1	0
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	0	0	0	0	1
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	0	0	0
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	1	0	0	0	0	0	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	1	0	0	1	0	0
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	0	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	0	0	0	0	0
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	0	0	0	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	1	1	0	1	1	1	0
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	0	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	0	0	0	0	0
34	Robbery	La Filipina	Tagum City	0	0	0	0	0	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	0	0	0	0	0
36	Robbery	Apokon	Tagum City	0	0	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	1	0	1	0	1	0
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	0	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	0	0	0	0	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
43	Robbery	Magugpo West	Tagum City	0	1	0	0	0	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	0	0	0	0
45	Theft	Santo NiV±o (Pob.)	Panabo City	0	0	0	1	1	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	1	0	0	0	1
47	Physical Injuries	Magugpo Poblacion	Tagum City	1	0	0	1	0	0	0
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	0	0	0
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	0	0

	crime	barangay	city	Pawnshop	Pharmacy	Police Station	Post Office	Private Office	Recreational Area
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	1	1	0	1	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	0	1	0	1	1	1
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	0	0	0
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	0	0	0
5	Drug Related Incident (RA	New Visayas	Panabo City	0	0	0	0	0	0
6	Theft	Mambago-A	Samal City	0	0	0	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	1	1	1	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	0	0	0	0	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	0	0	0
13	Theft	Magugpo South	Tagum City	0	0	0	0	0	0
14	Theft	Magugpo Poblacion	Tagum City	0	1	0	0	0	0
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	0	0	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	0	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	0	0	0	0	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	0	0	0	0	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	0	0	0	0
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	0	0	0	0	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	1	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	0	1	1	0	0
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	0	0	0	0
34	Robbery	La Filipina	Tagum City	0	0	0	0	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	0	0	0	0
36	Robbery	Apokon	Tagum City	0	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	1	0	1	0	1
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	0	0	1
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	0	0	0	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	0	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	0	0	0
45	Theft	Santo NiÝ±o (Pob.)	Panabo City	0	0	0	0	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	1	0	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	1	1	0	0	1	1
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	0	0
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	0

	crime	barangay	city	Residential Building	Restaurant	Road	School	Sports Center	Tourist Attraction	Transport Terminal
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	1	0	1	0	0	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	0	1	0	1	0	1	0
3	Murder/Homicide	Magugpo North	Tagum City	0	1	0	1	0	0	0
4	Physical Injuries	Magugpo North	Tagum City	0	1	0	1	0	0	0
5	Drug Related Incident (RA	New Visayas	Panabo City	1	0	0	0	0	0	0
6	Theft	Mambago-A	Samal City	1	0	0	1	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	1	0	0	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	0	1	0	0	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	1	0	0	1	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	1	1	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	1	0	1	0	0	0
13	Theft	Magugpo South	Tagum City	0	1	0	1	0	0	0
14	Theft	Magugpo Poblacion	Tagum City	0	1	0	1	0	0	0
15	Drug Related Incident (RA	Cagangohan	Panabo City	1	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	1	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	1	1	0	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	0	0	0
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	1	0	0	0	0	0	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	1	0	0	0	0	0	0
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	0	0	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	0	0	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	1	0	0	0	0	0	0
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	1	0	0	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	1	1	1	0	1	0	1
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	0	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	1	1	0	0	0
34	Robbery	La Filipina	Tagum City	1	0	0	0	0	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	1	1	0	0	0
36	Robbery	Apokon	Tagum City	1	0	0	1	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	0	1	0	0	1	0	0
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	1	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	0	0	0
40	Theft	San Pedro	Panabo City	0	0	0	0	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	1	0	0	1	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	0	0	0	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	0	0	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	1	0	0	0
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	0	0	1	0	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	1	0	0	0	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	0	1	0	1	0	1	0
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	0	0	0
50	Murder/Homicide	Licup	Samal City	0	0	0	1	0	0	0

	crime	barangay	city	php-usd-rate	PSE-index-Close	Education, Baccalauate graduate	Education,College undergraduate	Education,Elementary	Education, High school
1	Murder/Homicide	Magugpo Poblacion	Tagum City	50.546	8071.4702	395.5	304	353.5	810.5
2	Physical Injuries	Magugpo Poblacion	Tagum City	50.546	8071.4702	395.5	304	353.5	810.5
3	Murder/Homicide	Magugpo North	Tagum City	50.546	8071.4702	1168	897.5	1044	2392.5
4	Physical Injuries	Magugpo North	Tagum City	50.546	8071.4702	1168	897.5	1044	2392.5
5	Drug Related Incident (RA	New Visayas	Panabo City	50.582	8018.0498	1522	1329.5	2094.5	4698.5
6	Theft	Mambago-A	Samal City	50.582	8018.0498	99	106	383	493
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	50.582	8018.0498	395.5	304	353.5	810.5
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	50.582	8018.0498	1354	1040.5	1210.5	2773.5
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	50.502	7906.6001	5037	3869.5	4502.5	10318.5
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	50.502	7906.6001	1520	1328	2091.5	4692
11	Murder/Homicide	San Isidro	Tagum City	50.502	7906.6001	599.5	460.5	536	1228
12	Physical Injuries	Magugpo South	Tagum City	50.502	7906.6001	1354	1040.5	1210.5	2773.5
13	Theft	Magugpo South	Tagum City	50.502	7906.6001	1354	1040.5	1210.5	2773.5
14	Theft	Magugpo Poblacion	Tagum City	50.502	7906.6001	395.5	304	353.5	810.5
15	Drug Related Incident (RA	Cagangohan	Panabo City	50.397	7872.6499	1266	1106	1741.5	3907.5
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	50.397	7872.6499	1520	1328	2091.5	4692
17	Carnapping (R.A. 6539)	Apokon	Tagum City	50.397	7872.6499	3717.5	2856	3323.5	7615.5
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	50.397	7872.6499	1924	1478	1720	3941
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	50.422	7876.6602	2164.5	1663	1935	4434
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	50.422	7876.6602	1178.5	1030	1622.5	3639.5
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	50.422	7876.6602	1746	1341.5	1560.5	3575.5
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	50.365	7932.8198	4870	3741.5	4353.5	9976.5
23	Theft	La Filipina	Tagum City	50.365	7932.8198	1924	1478	1720	3941
24	Murder/Homicide	Madaum	Tagum City	50.365	7932.8198	1340.5	1029.5	1198	2745.5
25	Theft	Kiotoy	Panabo City	50.185	7992.27	138	120.5	190	425.5
26	Robbery	Magugpo South	Tagum City	50.185	7992.27	1354	1040.5	1210.5	2773.5
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	50.185	7992.27	395.5	304	353.5	810.5
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	50.31	7986.5098	4870	3741.5	4353.5	9976.5
29	Carnapping (R.A. 6539)	Apokon	Tagum City	50.31	7986.5098	3717.5	2856	3323.5	7615.5
30	Physical Injuries	New Pandan (Pob.)	Panabo City	50.31	7986.5098	609.5	533	839	1882
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	50.388	7985.8301	4870	3741.5	4353.5	9976.5
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	50.388	7985.8301	599.5	460.5	536	1228
33	Murder/Homicide	New Malitbog	Panabo City	50.388	7985.8301	301	263	414	929
34	Robbery	La Filipina	Tagum City	50.388	7985.8301	1924	1478	1720	3941
35	Physical Injuries	New Malitbog	Panabo City	50.388	7985.8301	301	263	414	929
36	Robbery	Apokon	Tagum City	50.388	7985.8301	3717.5	2856	3323.5	7615.5
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	50.388	7985.8301	395.5	304	353.5	810.5
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	50.688	7928.4302	602.5	527	829.5	1861
39	Drug Related Incident (RA	Licup	Samal City	50.688	7928.4302	48.5	51.5	185.5	239
40	Theft	San Pedro	Panabo City	50.688	7928.4302	385	336.5	530	1189.5
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	50.688	7928.4302	4870	3741.5	4353.5	9976.5
42	Carnapping (R.A. 6539)	Apokon	Tagum City	50.688	7928.4302	3717.5	2856	3323.5	7615.5
43	Robbery	Magugpo West	Tagum City	50.688	7928.4302	1746	1341.5	1560.5	3575.5
44	Physical Injuries	Magugpo East	Tagum City	50.688	7928.4302	1803.5	1385.5	1612	3694.5
45	Theft	Santo Niv±o (Pob.)	Panabo City	50.688	7928.4302	398	348	548	1228.5
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	50.688	7928.4302	602.5	527	829.5	1861
47	Physical Injuries	Magugpo Poblacion	Tagum City	50.688	7928.4302	395.5	304	353.5	810.5
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	50.688	7928.4302	2164.5	1663	1935	4434
49	Robbery	Magugpo East	Tagum City	50.688	7928.4302	1803.5	1385.5	1612	3694.5
50	Murder/Homicide	Licup	Samal City	51.009	7962.1201	48.5	51.5	185.5	239

	crime	barangay	city	Education, No grade completed	Education, Out of school youth	Education, Post baccalaureate	Education, Postsecondary	Household, number of households	Housing, dwelling tenure status, Own house rent lot
1	Murder/Homicide	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
2	Physical Injuries	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
3	Murder/Homicide	Magugpo North	Tagum City	31.5	348	20.5	261.5	2243	32
4	Physical Injuries	Magugpo North	Tagum City	31.5	348	20.5	261.5	2243	32
5	Drug Related Incident (RA	New Visayas	Panabo City	49.5	611.5	14	293.5	3959	56
6	Theft	Mambago-A	Samal City	13	67.5	1	21	476.5	7
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	36.5	403.5	24	303	2600.5	37
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	136.5	1500.5	88.5	1126.5	9673.5	137
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	49.5	610.5	14	293	3953.5	56
11	Murder/Homicide	San Isidro	Tagum City	16	178.5	10.5	134	1151.5	16
12	Physical Injuries	Magugpo South	Tagum City	36.5	403.5	24	303	2600.5	37
13	Theft	Magugpo South	Tagum City	36.5	403.5	24	303	2600.5	37
14	Theft	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
15	Drug Related Incident (RA	Cagangohan	Panabo City	41	508.5	12	244	3292	46.5
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	49.5	610.5	14	293	3953.5	56
17	Carnapping (R.A. 6539)	Apokon	Tagum City	100.5	1107	65.5	831.5	7140.5	101.5
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	52	573	34	430	3694.5	52.5
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	58.5	645	38	484	4157.5	59
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	38.5	473.5	11	227.5	3066.5	43.5
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	47.5	520	30.5	390.5	3352.5	47.5
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	132	1450.5	85.5	1089	9353.5	133
23	Theft	La Filipina	Tagum City	52	573	34	430	3694.5	52.5
24	Murder/Homicide	Madaum	Tagum City	36.5	399.5	23.5	300	2573.5	36.5
25	Theft	Kiotoy	Panabo City	4.5	55.5	1	26.5	359	5
26	Robbery	Magugpo South	Tagum City	36.5	403.5	24	303	2600.5	37
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	132	1450.5	85.5	1089	9353.5	133
29	Carnapping (R.A. 6539)	Apokon	Tagum City	100.5	1107	65.5	831.5	7140.5	101.5
30	Physical Injuries	New Pandan (Pob.)	Panabo City	20	245	6	117.5	1586	22.5
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	132	1450.5	85.5	1089	9353.5	133
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	16	178.5	10.5	134	1151.5	16
33	Murder/Homicide	New Malitbog	Panabo City	10	121	3	58	783	11
34	Robbery	La Filipina	Tagum City	52	573	34	430	3694.5	52.5
35	Physical Injuries	New Malitbog	Panabo City	10	121	3	58	783	11
36	Robbery	Apokon	Tagum City	100.5	1107	65.5	831.5	7140.5	101.5
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	20	242	6	116.5	1568	22
39	Drug Related Incident (RA	Licup	Samal City	6	32.5	1	10	231	3
40	Theft	San Pedro	Panabo City	12.5	155	4	74.5	1002.5	14
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	132	1450.5	85.5	1089	9353.5	133
42	Carnapping (R.A. 6539)	Apokon	Tagum City	100.5	1107	65.5	831.5	7140.5	101.5
43	Robbery	Magugpo West	Tagum City	47.5	520	30.5	390.5	3352.5	47.5
44	Physical Injuries	Magugpo East	Tagum City	49	537.5	31.5	403.5	3463	49
45	Theft	Santo NiÝ±o (Pob.)	Panabo City	13	160	4	76.5	1035.5	15
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	20	242	6	116.5	1568	22
47	Physical Injuries	Magugpo Poblacion	Tagum City	11	118	7	88.5	760	11
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	58.5	645	38	484	4157.5	59
49	Robbery	Magugpo East	Tagum City	49	537.5	31.5	403.5	3463	49
50	Murder/Homicide	Licup	Samal City	6	32.5	1	10	231	3

	crime	barangay	city	Housing,dwelling tenure status,Own house rent,free lot with consent of owner	Housing,dwelling tenure status,Own house rent,free lot without consent of owner	Housing,dwelling tenure status,Own or owner,like possession of house and lot	Housing,dwelling tenure status,Rent house/ room including lot	Housing,dwelling tenure status,Rent ,free house and lot with consent of owner	Housing,dwelling tenure status,Rent ,free house and lot without consent of owner
1	Murder/Homicide	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
2	Physical Injuries	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
3	Murder/Homicide	Magugpo North	Tagum City	354.5	31	1526	122	174.5	3
4	Physical Injuries	Magugpo North	Tagum City	354.5	31	1526	122	174.5	3
5	Drug Related Incident (RA	New Visayas	Panabo City	625.5	54.5	2693.5	216	308	6
6	Theft	Mambago-A	Samal City	75.5	7	324.5	26	37	1
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	410.5	36	1769	142	202.5	4
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	1528.5	133	6581.5	527	752.5	14
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	624.5	54.5	2689.5	215.5	307.5	6
11	Murder/Homicide	San Isidro	Tagum City	182	16	783	62.5	89.5	2
12	Physical Injuries	Magugpo South	Tagum City	410.5	36	1769	142	202.5	4
13	Theft	Magugpo South	Tagum City	410.5	36	1769	142	202.5	4
14	Theft	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
15	Drug Related Incident (RA	Cagangohan	Panabo City	520	45.5	2240	179	256	5
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	624.5	54.5	2689.5	215.5	307.5	6
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1128	98.5	4858	389.5	555.5	10
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	583.5	51	2514	201.5	287	5
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	657	57.5	2828	226.5	323	6
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	484.5	42	2086.5	167	238.5	4
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	529.5	46	2280.5	183	260.5	5
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	1477.5	128.5	6363.5	509.5	727.5	14
23	Theft	La Filipina	Tagum City	583.5	51	2514	201.5	287	5
24	Murder/Homicide	Madaum	Tagum City	406.5	35.5	1751	140	200	4
25	Theft	Kiotoy	Panabo City	56.5	5	244	19.5	28	1
26	Robbery	Magugpo South	Tagum City	410.5	36	1769	142	202.5	4
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	1477.5	128.5	6363.5	509.5	727.5	14
29	Carnapping (R.A. 6539)	Apokon	Tagum City	1128	98.5	4858	389.5	555.5	10
30	Physical Injuries	New Pandan (Pob.)	Panabo City	250.5	22	1079	86.5	123.5	2
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	1477.5	128.5	6363.5	509.5	727.5	14
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	182	16	783	62.5	89.5	2
33	Murder/Homicide	New Malitbog	Panabo City	123.5	11	533	42.5	61	1
34	Robbery	La Filipina	Tagum City	583.5	51	2514	201.5	287	5
35	Physical Injuries	New Malitbog	Panabo City	123.5	11	533	42.5	61	1
36	Robbery	Apokon	Tagum City	1128	98.5	4858	389.5	555.5	10
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	247.5	21.5	1067	85.5	122	2
39	Drug Related Incident (RA	Licup	Samal City	36.5	3	157.5	12.5	18	0
40	Theft	San Pedro	Panabo City	158	14	681.5	54.5	78	1
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	1477.5	128.5	6363.5	509.5	727.5	14
42	Carnapping (R.A. 6539)	Apokon	Tagum City	1128	98.5	4858	389.5	555.5	10
43	Robbery	Magugpo West	Tagum City	529.5	46	2280.5	183	260.5	5
44	Physical Injuries	Magugpo East	Tagum City	547.5	47.5	2356	189	269.5	5
45	Theft	Santo Niv±o (Pob.)	Panabo City	163.5	14	704.5	56.5	80.5	2
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	247.5	21.5	1067	85.5	122	2
47	Physical Injuries	Magugpo Poblacion	Tagum City	120	10.5	517	41.5	59	1
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	657	57.5	2828	226.5	323	6
49	Robbery	Magugpo East	Tagum City	547.5	47.5	2356	189	269.5	5
50	Murder/Homicide	Licup	Samal City	36.5	3	157.5	12.5	18	0

	crime	barangay	city	Labor,Employed	Labor,In the Labor Force	Labor,Not in the Labor Force	Labor,Underemployed	Labor,Unemployed	Poverty,poverty incidence by employed
1	Murder/Homicide	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
2	Physical Injuries	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
3	Murder/Homicide	Magugpo North	Tagum City	3941	4152.5	2637.5	655	212	650.5
4	Physical Injuries	Magugpo North	Tagum City	3941	4152.5	2637.5	655	212	650.5
5	Drug Related Incident (RA	New Visayas	Panabo City	6747	7110	4515.5	1121	363.5	1113.5
6	Theft	Mambago-A	Samal City	750.5	791	502.5	124.5	40.5	123.5
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	4568.5	4814.5	3057.5	759.5	245.5	753.5
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	16995	17909.5	11374.5	2824.5	914.5	2804
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	6737.5	7100	4509	1120	362.5	1111.5
11	Murder/Homicide	San Isidro	Tagum City	2022.5	2131.5	1353.5	336	109	333.5
12	Physical Injuries	Magugpo South	Tagum City	4568.5	4814.5	3057.5	759.5	245.5	753.5
13	Theft	Magugpo South	Tagum City	4568.5	4814.5	3057.5	759.5	245.5	753.5
14	Theft	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
15	Drug Related Incident (RA	Cagangohan	Panabo City	5610.5	5913	3755	932.5	302	926
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	6737.5	7100	4509	1120	362.5	1111.5
17	Carnapping (R.A. 6539)	Apokon	Tagum City	12544	13219	8395.5	2084.5	675	2069.5
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	6491	6840	4344	1079	349.5	1071
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	7303	7696.5	4888	1213.5	393	1205
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	5226	5507.5	3497.5	868.5	281	862.5
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	5890	6206.5	3942	979	316.5	971.5
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	16432.5	17317	10998	2731	884.5	2711.5
23	Theft	La Filipina	Tagum City	6491	6840	4344	1079	349.5	1071
24	Murder/Homicide	Madaum	Tagum City	4521.5	4764.5	3026	751.5	243.5	746.5
25	Theft	Kiotoy	Panabo City	611	644	409	101.5	33	101
26	Robbery	Magugpo South	Tagum City	4568.5	4814.5	3057.5	759.5	245.5	753.5
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	16432.5	17317	10998	2731	884.5	2711.5
29	Carnapping (R.A. 6539)	Apokon	Tagum City	12544	13219	8395.5	2084.5	675	2069.5
30	Physical Injuries	New Pandan (Pob.)	Panabo City	2703	2848	1809	449	145.5	446
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	16432.5	17317	10998	2731	884.5	2711.5
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	2022.5	2131.5	1353.5	336	109	333.5
33	Murder/Homicide	New Malitbog	Panabo City	1334.5	1406.5	893	222	72	220
34	Robbery	La Filipina	Tagum City	6491	6840	4344	1079	349.5	1071
35	Physical Injuries	New Malitbog	Panabo City	1334.5	1406.5	893	222	72	220
36	Robbery	Apokon	Tagum City	12544	13219	8395.5	2084.5	675	2069.5
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	2672	2816	1788.5	444.5	144	441
39	Drug Related Incident (RA	Licup	Samal City	364.5	384	244	60.5	19.5	60
40	Theft	San Pedro	Panabo City	1708	1799.5	1142.5	283.5	92	281.5
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	16432.5	17317	10998	2731	884.5	2711.5
42	Carnapping (R.A. 6539)	Apokon	Tagum City	12544	13219	8395.5	2084.5	675	2069.5
43	Robbery	Magugpo West	Tagum City	5890	6206.5	3942	979	316.5	971.5
44	Physical Injuries	Magugpo East	Tagum City	6084.5	6412	4072	1011	327.5	1004
45	Theft	Santo NiÝ±o (Pob.)	Panabo City	1764.5	1859.5	1180.5	293.5	95	291
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	2672	2816	1788.5	444.5	144	441
47	Physical Injuries	Magugpo Poblacion	Tagum City	1334.5	1406.5	893	221.5	72	220
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	7303	7696.5	4888	1213.5	393	1205
49	Robbery	Magugpo East	Tagum City	6084.5	6412	4072	1011	327.5	1004
50	Murder/Homicide	Licup	Samal City	364.5	384	244	60.5	19.5	60

	crime	barangay	city	Poverty,poverty incidence by household	Poverty,poverty incidence by population	Poverty,poverty incidence by unemployed	Consumer Price Index - all items	Consumer Price Index - Alcoholic beverages and tobacco
1	Murder/Homicide	Magugpo Poblacion	Tagum City	126	718.5	13	159.2	183.6
2	Physical Injuries	Magugpo Poblacion	Tagum City	126	718.5	13	159.2	183.6
3	Murder/Homicide	Magugpo North	Tagum City	372.5	2122.5	38.5	159.2	183.6
4	Physical Injuries	Magugpo North	Tagum City	372.5	2122.5	38.5	159.2	183.6
5	Drug Related Incident (RA	New Visayas	Panabo City	657.5	3745.5	66	159.2	183.6
6	Theft	Mambago-A	Samal City	79.5	419.5	7.5	159.2	183.6
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	126	718.5	13	159.2	183.6
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	431.5	2460	44.5	159.2	183.6
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	1606	9151.5	166	159.6	183.7
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	656.5	3740	66	159.6	183.7
11	Murder/Homicide	San Isidro	Tagum City	191	1089	19.5	159.6	183.7
12	Physical Injuries	Magugpo South	Tagum City	431.5	2460	44.5	159.6	183.7
13	Theft	Magugpo South	Tagum City	431.5	2460	44.5	159.6	183.7
14	Theft	Magugpo Poblacion	Tagum City	126	718.5	13	159.6	183.7
15	Drug Related Incident (RA	Cagangohan	Panabo City	546.5	3114.5	54.5	159.6	183.7
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	656.5	3740	66	159.6	183.7
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1185.5	6755	122.5	159.6	183.7
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	613	3495	63	159.6	183.7
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	690	3933	71	159.6	183.7
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	509	2901	50.5	159.6	183.7
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	556.5	3171.5	57.5	159.6	183.7
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	1553	8848.5	160	159.6	183.7
23	Theft	La Filipina	Tagum City	613	3495	63	159.6	183.7
24	Murder/Homicide	Madaum	Tagum City	427.5	2434.5	44	159.6	183.7
25	Theft	Kiotoy	Panabo City	59.5	339	6	159.6	183.7
26	Robbery	Magugpo South	Tagum City	431.5	2460	44.5	159.6	183.7
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	126	718.5	13	159.6	183.7
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	1553	8848.5	160	159.6	183.7
29	Carnapping (R.A. 6539)	Apokon	Tagum City	1185.5	6755	122.5	159.6	183.7
30	Physical Injuries	New Pandan (Pob.)	Panabo City	263.5	1500	26.5	159.6	183.7
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	1553	8848.5	160	159.6	183.7
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	191	1089	19.5	159.6	183.7
33	Murder/Homicide	New Malitbog	Panabo City	130	741	13	159.6	183.7
34	Robbery	La Filipina	Tagum City	613	3495	63	159.6	183.7
35	Physical Injuries	New Malitbog	Panabo City	130	741	13	159.6	183.7
36	Robbery	Apokon	Tagum City	1185.5	6755	122.5	159.6	183.7
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	126	718.5	13	159.6	183.7
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	260.5	1483	26	159.6	183.7
39	Drug Related Incident (RA	Licup	Samal City	38.5	203.5	3.5	159.6	183.7
40	Theft	San Pedro	Panabo City	166	948	16.5	159.6	183.7
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	1553	8848.5	160	159.6	183.7
42	Carnapping (R.A. 6539)	Apokon	Tagum City	1185.5	6755	122.5	159.6	183.7
43	Robbery	Magugpo West	Tagum City	556.5	3171.5	57.5	159.6	183.7
44	Physical Injuries	Magugpo East	Tagum City	575	3276.5	59	159.6	183.7
45	Theft	Santo Niv±o (Pob.)	Panabo City	172	979.5	17.5	159.6	183.7
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	260.5	1483	26	159.6	183.7
47	Physical Injuries	Magugpo Poblacion	Tagum City	126	718.5	13	159.6	183.7
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	690	3933	71	159.6	183.7
49	Robbery	Magugpo East	Tagum City	575	3276.5	59	159.6	183.7
50	Murder/Homicide	Licup	Samal City	38.5	203.5	3.5	159.6	183.7

	crime	barangay	city	Consumer Price Index - transport	Consumer Price Index - Housing, water, electricity, gas, and other fuels	Consumer Price Index - Restaurant and miscellaneous goods and services	inflation rate	savings deposit interest rate	bank lending rates
1	Murder/Homicide	Magugpo Poblacion	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
2	Physical Injuries	Magugpo Poblacion	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
3	Murder/Homicide	Magugpo North	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
4	Physical Injuries	Magugpo North	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
5	Drug Related Incident (RA	New Visayas	Panabo City	140.2	143.6	137.4	2.2	0.707	5.673
6	Theft	Mambago-A	Samal City	140.2	143.6	137.4	2.2	0.707	5.673
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	140.2	143.6	137.4	2.2	0.707	5.673
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
11	Murder/Homicide	San Isidro	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
12	Physical Injuries	Magugpo South	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
13	Theft	Magugpo South	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
14	Theft	Magugpo Poblacion	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
15	Drug Related Incident (RA	Cagangohan	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
17	Carnapping (R.A. 6539)	Apokon	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
23	Theft	La Filipina	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
24	Murder/Homicide	Madaum	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
25	Theft	Kiotoy	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
26	Robbery	Magugpo South	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
29	Carnapping (R.A. 6539)	Apokon	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
30	Physical Injuries	New Pandan (Pob.)	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
33	Murder/Homicide	New Malitbog	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
34	Robbery	La Filipina	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
35	Physical Injuries	New Malitbog	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
36	Robbery	Apokon	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
39	Drug Related Incident (RA	Licup	Samal City	140.6	143.7	137.5	2.4	0.713	5.687
40	Theft	San Pedro	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
42	Carnapping (R.A. 6539)	Apokon	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
43	Robbery	Magugpo West	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
44	Physical Injuries	Magugpo East	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
45	Theft	Santo Niv±o (Pob.)	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	140.6	143.7	137.5	2.4	0.713	5.687
47	Physical Injuries	Magugpo Poblacion	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
49	Robbery	Magugpo East	Tagum City	140.6	143.7	137.5	2.4	0.713	5.687
50	Murder/Homicide	Licup	Samal City	140.6	143.7	137.5	2.4	0.713	5.687

	crime	barangay	city	time_epoch _After Midnight	time_epoch _After Work-Hours	time_epoch _Afternoon	time_epoch _Early Morning	time_epoch _Evening	time_epoch _Morning
1	Murder/Homicide	Magugpo Poblacion	Tagum City	1	0	0	0	0	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	1	0	0	0	0	0
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	0	1	0
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	0	1	0
5	Drug Related Incident (RA	New Visayas	Panabo City	0	0	1	0	0	0
6	Theft	Mambago-A	Samal City	0	0	1	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	0	1	0	0	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	0	0	0	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	1	0	0	0	0	0
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	0	0	0	0
11	Murder/Homicide	San Isidro	Tagum City	0	1	0	0	0	0
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	0	1	0
13	Theft	Magugpo South	Tagum City	0	1	0	0	0	0
14	Theft	Magugpo Poblacion	Tagum City	0	0	0	0	0	1
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	0	0	0	0	1
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	1	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	0	0	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	1	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	1	0	0	0	0	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	0	0	0	1	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	0	0	1	0	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	1	0	0	0	0	0
23	Theft	La Filipina	Tagum City	0	1	0	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	0	0	1	0
25	Theft	Kiotoy	Panabo City	0	0	0	0	0	1
26	Robbery	Magugpo South	Tagum City	0	0	0	0	0	1
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	0	0	0	1	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	1	0	0	0	0	0
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	0	0	0	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	1	0	0	0	0
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	1	0	0	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	1	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	0	0	0	1
34	Robbery	La Filipina	Tagum City	0	0	0	1	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	1	0	0	0
36	Robbery	Apokon	Tagum City	1	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	0	0	0	0	0	1
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	1	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	0	0	1	0
40	Theft	San Pedro	Panabo City	0	0	0	0	1	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	1	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	1	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	1	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	0	0	1
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	1	0	0	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	0	1	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	0	0	0	0	1	0
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	1	0	0	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	0	1	0
50	Murder/Homicide	Licup	Samal City	0	0	0	0	0	1

	crime	barangay	city	day_Friday	day_Monday	day_Saturday	day_Sunday	day_Thursday	day_Tuesday
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	0	0	1	0	0
2	Physical Injuries	Magugpo Poblacion	Tagum City	0	0	0	1	0	0
3	Murder/Homicide	Magugpo North	Tagum City	0	0	0	1	0	0
4	Physical Injuries	Magugpo North	Tagum City	0	0	0	1	0	0
5	Drug Related Incident (RA	New Visayas	Panabo City	0	1	0	0	0	0
6	Theft	Mambago-A	Samal City	0	1	0	0	0	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	0	0	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	0	0	0	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	0	0	1
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	1
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	0	0	1
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	0	0	1
13	Theft	Magugpo South	Tagum City	0	0	0	0	0	1
14	Theft	Magugpo Poblacion	Tagum City	0	0	0	0	0	1
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	0	0	0	0	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	0	0	0	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	0	0	0	0	0
19	Rape (Art. 266-A RC & R./	San Miguel (Camp 4)	Tagum City	0	0	0	0	1	0
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	0	0	0	1	0
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	0	0	0	1	0
22	Rape (Art. 266-A RC & R./	Mankilam	Tagum City	0	0	1	0	0	0
23	Theft	La Filipina	Tagum City	0	0	1	0	0	0
24	Murder/Homicide	Madaum	Tagum City	0	0	0	1	0	0
25	Theft	Kiotoy	Panabo City	0	1	0	0	0	0
26	Robbery	Magugpo South	Tagum City	0	1	0	0	0	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	0	0	0
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	1
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	0	0	0	1
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	0	0	0	0	1
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	0	0	0	0
32	Rape (Art. 266-A RC & R./	San Isidro	Tagum City	0	0	0	0	0	0
33	Murder/Homicide	New Malitbog	Panabo City	0	0	0	0	0	0
34	Robbery	La Filipina	Tagum City	0	0	0	0	0	0
35	Physical Injuries	New Malitbog	Panabo City	0	0	0	0	0	0
36	Robbery	Apokon	Tagum City	0	0	0	0	0	0
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	0	0	0	0	0	0
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	1	0	0	0	0	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	1	0	0	0
40	Theft	San Pedro	Panabo City	0	0	1	0	0	0
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	0	1	0	0	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	1	0	0	0
43	Robbery	Magugpo West	Tagum City	0	0	0	1	0	0
44	Physical Injuries	Magugpo East	Tagum City	0	0	0	1	0	0
45	Theft	Santo Niñ±o (Pob.)	Panabo City	0	0	0	1	0	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	0	0	1	0	0
47	Physical Injuries	Magugpo Poblacion	Tagum City	0	0	0	1	0	0
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	0	1	0	0
49	Robbery	Magugpo East	Tagum City	0	0	0	1	0	0
50	Murder/Homicide	Licup	Samal City	0	1	0	0	0	0

	crime	barangay	city	day_Wednesday	Weather_Clear	Weather_Cloudy	Weather_Rainy	day_night_daylight	day_night_nighttime
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	0	1	0	0	1
2	Physical Injuries	Magugpo Poblacion	Tagum City	0	0	1	0	0	1
3	Murder/Homicide	Magugpo North	Tagum City	0	0	1	0	0	1
4	Physical Injuries	Magugpo North	Tagum City	0	0	1	0	0	1
5	Drug Related Incident (RA	New Visayas	Panabo City	0	0	1	0	1	0
6	Theft	Mambago-A	Samal City	0	0	1	0	1	0
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	0	1	0	1	0
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	0	1	0	1	0
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	0	0	1	0	1
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	0	1	0	0	1
11	Murder/Homicide	San Isidro	Tagum City	0	0	0	1	1	0
12	Physical Injuries	Magugpo South	Tagum City	0	0	0	1	0	1
13	Theft	Magugpo South	Tagum City	0	0	0	1	1	0
14	Theft	Magugpo Poblacion	Tagum City	0	0	1	0	1	0
15	Drug Related Incident (RA	Cagangohan	Panabo City	1	0	1	0	1	0
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	1	0	0	1	1	0
17	Carnapping (R.A. 6539)	Apokon	Tagum City	1	0	0	1	1	0
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	1	0	1	0	0	1
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	0	0	1	0	0	1
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	1	0	0	0	1
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	1	0	0	0	1
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	0	0	0	1	0	1
23	Theft	La Filipina	Tagum City	0	0	0	1	1	0
24	Murder/Homicide	Madaum	Tagum City	0	0	1	0	0	1
25	Theft	Kiotoy	Panabo City	0	1	0	0	1	0
26	Robbery	Magugpo South	Tagum City	0	1	0	0	1	0
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	0	0	0	1
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	1	0	0	0	1
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	0	1	0	1	0
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	1	0	0	1	0
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	1	1	0	0	0	1
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	1	1	0	0	0	1
33	Murder/Homicide	New Malitbog	Panabo City	1	1	0	0	1	0
34	Robbery	La Filipina	Tagum City	1	1	0	0	0	1
35	Physical Injuries	New Malitbog	Panabo City	1	1	0	0	1	0
36	Robbery	Apokon	Tagum City	1	1	0	0	0	1
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	1	1	0	0	1	0
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	1	0	0	1	0
39	Drug Related Incident (RA	Licup	Samal City	0	0	1	0	0	1
40	Theft	San Pedro	Panabo City	0	0	1	0	0	1
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	1	0	0	1	0
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	0	0	1	0
43	Robbery	Magugpo West	Tagum City	0	1	0	0	1	0
44	Physical Injuries	Magugpo East	Tagum City	0	1	0	0	1	0
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	1	0	0	1	0
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	1	0	0	0	1
47	Physical Injuries	Magugpo Poblacion	Tagum City	0	0	1	0	0	1
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	0	1	0	0	1
49	Robbery	Magugpo East	Tagum City	0	0	1	0	0	1
50	Murder/Homicide	Licup	Samal City	0	1	0	0	1	0

	crime	barangay	city	placetype_ rural	placetype_ urban	Children Population	Teenage Population	Adult Population	Retiree Population
1	Murder/Homicide	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
2	Physical Injuries	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
3	Murder/Homicide	Magugpo North	Tagum City	0	1	1955.5	1873	5131	685
4	Physical Injuries	Magugpo North	Tagum City	0	1	1955.5	1873	5131	685
5	Drug Related Incident (RA	New Visayas	Panabo City	0	1	3677	3337.5	8807	1201.5
6	Theft	Mambago-A	Samal City	1	0	416	374	936.5	180
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	0	1	2267.5	2171	5948.5	794.5
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	0	1	8436	8076.5	22129.5	2957
10	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	1	3672.5	3333.5	8795	1200
11	Murder/Homicide	San Isidro	Tagum City	1	0	1004.5	961.5	2634	352
12	Physical Injuries	Magugpo South	Tagum City	0	1	2267.5	2171	5948.5	794.5
13	Theft	Magugpo South	Tagum City	0	1	2267.5	2171	5948.5	794.5
14	Theft	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
15	Drug Related Incident (RA	Cagangohan	Panabo City	0	1	3058.5	2775.5	7324	999
16	Drug Related Incident (RA	Gredu (Pob.)	Panabo City	0	1	3672.5	3333.5	8795	1200
17	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	6227	5961.5	16333	2182.5
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	0	1	3221.5	3084.5	8450.5	1129
19	Rape (Art. 266-A RC & R.A	San Miguel (Camp 4)	Tagum City	0	1	3625	3471	9509.5	1270
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	0	1	2849	2585.5	6821.5	930.5
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	0	1	2923.5	2798.5	7668	1025
22	Rape (Art. 266-A RC & R.A	Mankilam	Tagum City	0	1	8156.5	7809	21396.5	2859
23	Theft	La Filipina	Tagum City	0	1	3221.5	3084.5	8450.5	1129
24	Murder/Homicide	Madaum	Tagum City	0	1	2244	2148.5	5888	786.5
25	Theft	Kiotoy	Panabo City	1	0	333.5	302.5	798	108
26	Robbery	Magugpo South	Tagum City	0	1	2267.5	2171	5948.5	794.5
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	1	8156.5	7809	21396.5	2859
29	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	6227	5961.5	16333	2182.5
30	Physical Injuries	New Pandan (Pob.)	Panabo City	0	1	1473.5	1337	3528.5	481
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	1	8156.5	7809	21396.5	2859
32	Rape (Art. 266-A RC & R.A	San Isidro	Tagum City	1	0	1004.5	961.5	2634	352
33	Murder/Homicide	New Malitbog	Panabo City	1	0	727	660	1741.5	237.5
34	Robbery	La Filipina	Tagum City	0	1	3221.5	3084.5	8450.5	1129
35	Physical Injuries	New Malitbog	Panabo City	1	0	727	660	1741.5	237.5
36	Robbery	Apokon	Tagum City	0	1	6227	5961.5	16333	2182.5
37	Drug Related Incident (RA	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
38	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	1	1456.5	1322	3487.5	475.5
39	Drug Related Incident (RA	Licup	Samal City	1	0	201.5	181	454.5	87
40	Theft	San Pedro	Panabo City	0	1	931	845	2230	304
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	0	1	8156.5	7809	21396.5	2859
42	Carnapping (R.A. 6539)	Apokon	Tagum City	0	1	6227	5961.5	16333	2182.5
43	Robbery	Magugpo West	Tagum City	0	1	2923.5	2798.5	7668	1025
44	Physical Injuries	Magugpo East	Tagum City	0	1	3020.5	2892	7923.5	1058.5
45	Theft	Santo Niv±o (Pob.)	Panabo City	0	1	962	873	2302.5	314.5
46	Drug Related Incident (RA	J.P. Laurel	Panabo City	0	1	1456.5	1322	3487.5	475.5
47	Physical Injuries	Magugpo Poblacion	Tagum City	0	1	662	635	1738	232
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	0	1	3625	3471	9509.5	1270
49	Robbery	Magugpo East	Tagum City	0	1	3020.5	2892	7923.5	1058.5
50	Murder/Homicide	Licup	Samal City	1	0	201.5	181	454.5	87

	crime	barangay	city	Female Children Population	Female Teenage Population	Female Adult Population	Female Retiree Population	Male Children Population	Male Teenage Population	Male Adult Population	Male Retiree Population
1	Murder/Homicide	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
2	Physical Injuries	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
3	Murder/Homicide	Magugpo North	Tagum City	947.5	932	2550	369	1010	941	2581.5	317.5
4	Physical Injuries	Magugpo North	Tagum City	947.5	932	2550	369	1010	941	2581.5	317.5
5	Drug Related Incident (RA 9	New Visayas	Panabo City	1795.5	1651	4304	632	1882	1686.5	4502.5	569.5
6	Theft	Mambago-A	Samal City	202	177	451.5	93.5	214	196.5	487	87
7	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
8	Carnapping (R.A. 6539)	Magugpo South	Tagum City	1097.5	1080.5	2955	427	1170.5	1091	2993	367.5
9	Carnapping (R.A. 6539)	Visayan Village	Tagum City	4083	4019.5	10994	1588.5	4352.5	4057.5	11134	1368
10	Drug Related Incident (RA 9	Gredu (Pob.)	Panabo City	1793	1649	4298	631.5	1880	1684.5	4496	569
11	Murder/Homicide	San Isidro	Tagum City	486.5	478	1308.5	189	518	483	1325	162.5
12	Physical Injuries	Magugpo South	Tagum City	1097.5	1080.5	2955	427	1170.5	1091	2993	367.5
13	Theft	Magugpo South	Tagum City	1097.5	1080.5	2955	427	1170.5	1091	2993	367.5
14	Theft	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
15	Drug Related Incident (RA 9	Cagangohan	Panabo City	1493	1373.5	3580.5	525.5	1565	1403	3744.5	473.5
16	Drug Related Incident (RA 9	Gredu (Pob.)	Panabo City	1793	1649	4298	631.5	1880	1684.5	4496	569
17	Carnapping (R.A. 6539)	Apokon	Tagum City	3013	2967	8113	1172.5	3213	2995	8219.5	1009
18	Carnapping (R.A. 6539)	La Filipina	Tagum City	1559.5	1534.5	4197.5	606.5	1662	1549.5	4252.5	522.5
19	Rape (Art. 266-A RC & R.A.	San Miguel (Camp 4)	Tagum City	1755	1727	4723.5	683.5	1870.5	1744	4784	588
20	Murder/Homicide	San Francisco (Pob.)	Panabo City	1390.5	1279.5	3333.5	489.5	1458	1306	3487.5	441.5
21	Carnapping (R.A. 6539)	Magugpo West	Tagum City	1415	1393	3810.5	550	1508	1406.5	3860	473.5
22	Rape (Art. 266-A RC & R.A.	Mankilam	Tagum City	3948	3886.5	10629	1536	4209	3923	10766.5	1322.5
23	Theft	La Filipina	Tagum City	1559.5	1534.5	4197.5	606.5	1662	1549.5	4252.5	522.5
24	Murder/Homicide	Madaum	Tagum City	1086	1069.5	2925	423	1158	1079.5	2962.5	363.5
25	Theft	Kiotoy	Panabo City	162	149.5	389.5	58	170	153	408	51
26	Robbery	Magugpo South	Tagum City	1097.5	1080.5	2955	427	1170.5	1091	2993	367.5
27	Carnapping (R.A. 6539)	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
28	Carnapping (R.A. 6539)	Mankilam	Tagum City	3948	3886.5	10629	1536	4209	3923	10766.5	1322.5
29	Carnapping (R.A. 6539)	Apokon	Tagum City	3013	2967	8113	1172.5	3213	2995	8219.5	1009
30	Physical Injuries	New Pandan (Pob.)	Panabo City	719	661.5	1724.5	253.5	753	675.5	1803	229
31	Carnapping (R.A. 6539)	Mankilam	Tagum City	3948	3886.5	10629	1536	4209	3923	10766.5	1322.5
32	Rape (Art. 266-A RC & R.A.	San Isidro	Tagum City	486.5	478	1308.5	189	518	483	1325	162.5
33	Murder/Homicide	New Malitbog	Panabo City	355	326.5	852	125	372	333	890.5	112.5
34	Robbery	La Filipina	Tagum City	1559.5	1534.5	4197.5	606.5	1662	1549.5	4252.5	522.5
35	Physical Injuries	New Malitbog	Panabo City	355	326.5	852	125	372	333	890.5	112.5
36	Robbery	Apokon	Tagum City	3013	2967	8113	1172.5	3213	2995	8219.5	1009
37	Drug Related Incident (RA 9	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
38	Drug Related Incident (RA 9	J.P. Laurel	Panabo City	711	654	1703.5	250	745.5	668	1783	225.5
39	Drug Related Incident (RA 9	Licup	Samal City	98.5	86	218.5	45.5	104	95.5	235.5	42.5
40	Theft	San Pedro	Panabo City	454	418	1090.5	159.5	476.5	427	1138.5	144
41	Carnapping (R.A. 6539)	Mankilam	Tagum City	3948	3886.5	10629	1536	4209	3923	10766.5	1322.5
42	Carnapping (R.A. 6539)	Apokon	Tagum City	3013	2967	8113	1172.5	3213	2995	8219.5	1009
43	Robbery	Magugpo West	Tagum City	1415	1393	3810.5	550	1508	1406.5	3860	473.5
44	Physical Injuries	Magugpo East	Tagum City	1462	1439	3936.5	568.5	1558	1452	3986.5	490
45	Theft	Santo Niv±o (Pob.)	Panabo City	469.5	432	1125.5	165.5	492	441	1177	149.5
46	Drug Related Incident (RA 9	J.P. Laurel	Panabo City	711	654	1703.5	250	745.5	668	1783	225.5
47	Physical Injuries	Magugpo Poblacion	Tagum City	320.5	315	863	124.5	341.5	318.5	874.5	107
48	Physical Injuries	San Miguel (Camp 4)	Tagum City	1755	1727	4723.5	683.5	1870.5	1744	4784	588
49	Robbery	Magugpo East	Tagum City	1462	1439	3936.5	568.5	1558	1452	3986.5	490
50	Murder/Homicide	Licup	Samal City	98.5	86	218.5	45.5	104	95.5	235.5	42.5

Appendix D. Weather Data – Data Gathering Code

Code for downloading weather data from World Weather Online.

```
from selenium import webdriver
import csv

# Create a new instance of the Chrome driver
driver = webdriver.Chrome('/usr/local/bin/chromedriver')

# get input data
dates_list = open("dates_1.txt").read().splitlines()
regions_urls_list = open("region_urls.txt").read().splitlines()
regions_place_list = open("regions_place.txt").read().splitlines()

# go to the weatheronline
loop_count = 0

for url in regions_urls_list:
    region = regions_place_list[loop_count]
    driver.get(url)

    for date in dates_list:
        # # date format: day-month-year date = '01/08/2017'
        driver.find_element_by_id(
            "ctl00_MainContentHolder_txtPastDate").send_keys(date)
        driver.find_element_by_id(
            "ctl00_MainContentHolder_butShowPastWeather").click()

        # extract weather data
        # time
        time = driver.find_element_by_class_name("tb_date")
        time = time.text.split('\n')
        # print(time)

        # weather
        weather = driver.find_element_by_class_name("tb_weather")
        weather_list = weather.text.split('\n')
        weather_name = weather.find_elements_by_tag_name("img")
        for name in weather_name:
            weather_list.append(name.get_attribute('alt'))
        weather_list = list(filter(None, weather_list))
        # print(weather_list)

```

```
        # temperature
        temp = driver.find_element_by_class_name("tb_temp")
        temp = temp.text.split('\n')
        # print(temp)

        # temperature - Feels like
        temp_feels = driver.find_element_by_class_name("tb_feels")
        temp_feels = temp_feels.text.split('\n')
        # print(temp_feels)

        # wind and direction
        wind = driver.find_element_by_class_name("tb_wind")
        wind = wind.text.split('\n')
        direction = ['Direction']
        for item in wind:
            if 'Wind' in item or 'km/h' in item:
                next
            else:
                direction.append(item)
                wind.remove(item)
        # print(wind)
        # print(direction)

        # cloud
        cloud = driver.find_element_by_class_name("tb_cloud")
        cloud = cloud.text.split('\n')
        # print(cloud)

        # humidity
        humidity = driver.find_element_by_class_name("tb_humidity")
        humidity = humidity.text.split('\n')
        # print(humidity)

        # precipitation
        precip = driver.find_element_by_class_name("tb_precip")
        precip = precip.text.split('\n')
        # print(precip)

        # pressure
        pressure = driver.find_element_by_class_name("tb_pressure")
        pressure = pressure.text.split('\n')
        # print(pressure)

        # # sunrise and sunset
        # sun = driver.find_element_by_class_name("wh_prime_item_3")
        # sun = sun.find_elements_by_class_name("info_item")
        # sun = sun[1].text.split('\n')
```

```
    # sunrise = '00:00 AM'
    # sunset = '00:00 PM'
    # for item in sun:
    #     new = item.split(': ')
    #     if 'rise' in new[0]:
    #         sunrise = new[1]
    #     if 'set' in new[0]:
    #         sunset = new[1]
    # # print(sunrise)
    # # print(sunset)

    # save data to csv
    csv_columns = [
        'Region','Date',
        time[0],weather_list[0],
        temp[0],temp_feels[0],
        wind[0],direction[0],
        cloud[0],humidity[0],
        precip[0],pressure[0],
        # 'Sunrise', 'Sunset'
    ]

    instance_list =[]
    counter = 1
    while counter < 9:
        single_dict = {
            csv_columns[0]: region,
            csv_columns[1]: date,
            csv_columns[2]: time[counter],
            csv_columns[3]: weather_list[counter],
            csv_columns[4]: temp[counter],
            csv_columns[5]: temp_feels[counter],
            csv_columns[6]: wind[counter],
            csv_columns[7]: direction[counter],
            csv_columns[8]: cloud[counter],
            csv_columns[9]: humidity[counter],
            csv_columns[10]: precip[counter],
            csv_columns[11]: pressure[counter]
        }
        instance_list.append(single_dict)
        counter+=1

    # sun_dict = {
    #     csv_columns[0]: region,
    #     csv_columns[1]: date,
    #     csv_columns[2]: sunrise,
    #     csv_columns[3]: sunset
```

```
        # }
        # instance_list.append(sun_dict)

        csv_file = "weather_davaodelnorte_data.csv"
        # csv_file = "sunrise_sunset_davaodelnorte_data.csv"
        try:
            with open(csv_file, 'a') as csvfile:
                writer = csv.DictWriter(csvfile, fieldnames=csv_columns)
                if date == dates_list[0] and loop_count == 0:
                    writer.writeheader()
                for data in instance_list:
                    writer.writerow(data)
        except IOError:
            print("I/O error")

    loop_count+=1

# close driver
driver.close()
driver.quit()
```

Appendix E. Places Data – Data Gathering Code

Code for downloading places data from Overpass API.

```
import csv
from OSMPythonTools.overpass import Overpass
places_dict = []
with open('place.csv') as csvfile:
    reader = csv.DictReader(csvfile)
    for row in reader:
        instance = {
            'lat' : row['lat'],
            'lng' : row['lng']
        }
        places_dict.append(instance)
elements = ['way','rel','node']
distance_min = 10
distance_max = 200
overpass = Overpass()
csv_columns = ['latitude','longitude','distance','places']

def get_maps():
    loop_count = 0
    for place in places_dict:
        lat = float(place['lat'])
        lng = float(place['lng'])
        vicinity = []
        str_query_area = 'is_in({lat:.5f},{lng:.3f}); out body;'.format(lat=lat,lng=lng)
        result_area = overpass.query(str_query_area)
        y = 0
        while y < len(result_area.elements()):
            place_instance = {
                'latitude': lat,
                'longitude': lng,
                'distance': 0,
                'places': result_area.elements()[y].tags()
            }
            y+=1
            not_relevant = False
            for item in donot_append:
                if item in str(place_instance['places']):
                    not_relevant = True
                    break
            if not_relevant: continue
            match = [x for x in vicinity if x['places'] == place_instance['places']]
            if not match:
```

```
                vicinity.append(place_instance)

        for element in elements:
            #element way|node|rel[tag filter](around:within meter,latitude,longitudes)[tag=value filter]
            # for tag in element_filters:
            iter_distance = distance_min
            while iter_distance <= distance_max:
                # str_query = '{element}[{tag}](around:{distance},{lat:.5f},{lng:.3f}); out body;'.format(
                # element=element,tag=tag,distance=iter_distance,lat=lat,lng=lng)
                str_query = '{element}(around:{distance},{lat:.5f},{lng:.3f}); out body;'.format(
                    element=element,distance=iter_distance,lat=lat,lng=lng)
                result = overpass.query(str_query)
                i = 0
                while i < len(result.elements()):
                    place_instance = {
                        'latitude': lat,
                        'longitude': lng,
                        'distance': iter_distance,
                        'places': result.elements()[i].tags()
                    }
                    i+=1
                    match = [x for x in vicinity if x['places'] == place_instance['places']]
                    if not match:
                        vicinity.append(place_instance)
                iter_distance+=distance_min
        if not vicinity:
            vicinity.append({
                'latitude': lat,
                'longitude': lng,
                'distance': 0,
                'places': 'none'
            })
        csv_file = "places_crime.csv"
        try:
            with open(csv_file, 'a') as csvfile:
                writer = csv.DictWriter(csvfile, fieldnames=csv_columns)
                if loop_count == 0:
                    writer.writeheader()
                    loop_count+=1
                for data in vicinity:
                    writer.writerow(data)
        except IOError:
            print("I/O error")

get_maps()
```

Appendix F. Raw Crime Data – Data Gathering Code

Code for downloading crime data from the PNP website. The right to use the data within lawful purposes was included in the disclaimer section of the PNP website – (*https://didm.pnp.gov.ph/index.php/disclaimer*) (Philippine National Police, 2019). This project was an independent research and not, in anyway, endorsed by the Philippine National Police.

```
import urllib.request
import json

urlList = [
    {
        "url":"https://www.bantaykrimen.com/data.php?regionid=110000000&province=0",
        "name":"region11.json"
    }
]

for x in range(0, len(urlList)):
    crimedata = urllib.request.urlopen(urlList[x]["url"])
    readcrimedata = crimedata.read()
    jsoncrimedata = json.loads(readcrimedata)
    with open(urlList[x]["name"], 'w') as outfile:
        json.dump(jsoncrimedata, outfile)
```

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Appendix G. Mobile Application Results Graph Code

Code to show graph of crime probabilities in the results window.

```
package com.angelalmuenda.dangerpredict;

import android.support.v4.content.ContextCompat;
import android.support.v7.app.AppCompatActivity;

import android.os.Bundle;
import android.widget.TextView;

import com.github.mikephil.charting.charts.BarChart;
import com.github.mikephil.charting.components.AxisBase;
import com.github.mikephil.charting.components.XAxis;
import com.github.mikephil.charting.components.YAxis;
import com.github.mikephil.charting.data.BarData;
import com.github.mikephil.charting.data.BarDataSet;
import com.github.mikephil.charting.data.BarEntry;
import com.github.mikephil.charting.formatter.IAxisValueFormatter;
import com.github.mikephil.charting.interfaces.datasets.IBarDataSet;

import java.util.ArrayList;

public class PredictionBarGraph extends AppCompatActivity {
    @Override
    protected void onCreate(Bundle savedInstanceState) {
        super.onCreate(savedInstanceState);
        setContentView(R.layout.activity_prediction_bar_graph);
        TextView title = (TextView) findViewById(R.id.textTitle);
        String titleText= getIntent().getStringExtra("TITLE_STR");
        title.setText(titleText);

        TextView assess = (TextView) findViewById(R.id.textAssess);
        String assessText= getIntent().getStringExtra("ASSESS_STR");
        assess.setText(assessText);
        ArrayList<BarEntry> values = new ArrayList<>();
        final String[] mLabels = {
                "Carnapping",
                "Drug Related Incident",
                "Murder/Homicide",
                "Physical Injuries",
                "Rape",
                "Robbery",
```

```
                "Theft"
        };
        for (int i = 0; i < 7; i++) {
            String name2 = new String();
            name2 = String.format("%s_%s","CRIME_VALUE",String.valueOf(i));
            Float temp1 = new Float(getIntent().getStringExtra(name2));
            values.add(new BarEntry(i, temp1));
        }
        BarChart chart = findViewById(R.id.crime_chart);
        chart.setDrawBarShadow(false);
        chart.setDrawValueAboveBar(true);
        chart.getLegend().setEnabled(false);
        chart.getDescription().setEnabled(false);
        chart.setPinchZoom(false);
        chart.setDrawGridBackground(false);
        chart.getAxisRight().setEnabled(false);
        chart.setFitBars(true);

        XAxis xAxis = chart.getXAxis();
        xAxis.setPosition(XAxis.XAxisPosition.BOTTOM);
        xAxis.setDrawGridLines(false);
        xAxis.setGranularity(1f); // only intervals of 1 day
        xAxis.setLabelCount(8);
        xAxis.setLabelRotationAngle(270.0f);
        xAxis.setValueFormatter(new IAxisValueFormatter(){
            @Override
            public String getFormattedValue(float value, AxisBase axis) {
                return mLabels[(int) value];
            }
        });
        YAxis leftAxis = chart.getAxisLeft();
        leftAxis.setLabelCount(8, false);
        leftAxis.setPosition(YAxis.YAxisLabelPosition.OUTSIDE_CHART);
        leftAxis.setSpaceTop(15f);
        leftAxis.setAxisMinimum(0f); // this replaces setStartAtZero(true)
        BarDataSet set = new BarDataSet(values,"");
        set.setDrawIcons(false);
        set.setColors(new int[]{
                ContextCompat.getColor(this, android.R.color.holo_orange_light),
                ContextCompat.getColor(this, android.R.color.holo_blue_bright),
                ContextCompat.getColor(this, android.R.color.holo_green_light),
                ContextCompat.getColor(this, android.R.color.holo_purple),
                ContextCompat.getColor(this, android.R.color.holo_red_light),
                ContextCompat.getColor(this, android.R.color.holo_blue_dark),
```

```
                ContextCompat.getColor(this, android.R.color.holo_red_dark),
        });
        ArrayList<IBarDataSet> dataSets = new ArrayList<>();
        dataSets.add(set);
        BarData data = new BarData(dataSets);
        data.setValueTextSize(10f);
        data.setBarWidth(0.9f);
        chart.setData(data);
    }
}
```

Appendix H. Mobile Implementation - Data Validation Code

Code to check if all required data are correctly set before sending to the web server.

```
private boolean allDataValid() {
    String title = new String();
    String message = new String();
    boolean isValid = true;
    if (maSocialMap.selectedLocation == "") {
        title = "Selected Location Invalid";
        message = "Please change the map location to point inside city boundaries.";
        isValid = false;
    }
    else if (maTimeDayWeek.dayGroup.getCheckedRadioButtonId() == -1) {
        title = "No Day of Week selected";
        message = "Please indicate day.";
        isValid = false;
    }
    else if (maTimeDayWeek.timeGroup.getCheckedRadioButtonId() == -1) {
        title = "No Time of Day selected";
        message = "Please indicate time.";
        isValid = false;
    }
    else if (maTimeDayWeek.daylightGroup.getCheckedRadioButtonId() == -1) {
        title = "No Day or Night Stay selected";
        message = "Please indicate stay.";
        isValid = false;
    }
    else if (!maPlaces.selectedPlaces()) {
        title = "No Type of Place selected";
        message = "Please select one or more type of places you see around the vicinity.";
        isValid = false;
    }
    else if (maWeather.weatherGroup.getCheckedRadioButtonId() == -1) {
        title = "No Type of Weather selected";
        message = "Please indicate if weather will be clear, cloudy, or rainy.";
        isValid = false;
    }
    if (!isValid) {
        AlertDialog.Builder builder = new AlertDialog.Builder(this);
        builder.setMessage(message).setTitle(title);
        AlertDialog dialog = builder.create();
        dialog.show();
        spinner.setVisibility(View.GONE);
        pData.buttonPredict.setEnabled(true);
        return isValid;
    }
    allData = new ArrayMap<String,String>();
    allData.put("location", maSocialMap.selectedLocation);
    allData.put(pData.ind_vars[0], String.valueOf(uniMarker.getPosition().longitude));
```

```
    allData.put(pData.ind_vars[1], String.valueOf(uniMarker.getPosition().latitude));
    allData.put(pData.ind_vars[2],maWeather.textTemp.getText().toString());
    allData.put(pData.ind_vars[3],maWeather.textFeels.getText().toString());
    allData.put(pData.ind_vars[4],maWeather.textWind.getText().toString());
    allData.put(pData.ind_vars[5],maWeather.textCloud.getText().toString());
    allData.put(pData.ind_vars[6],maWeather.textHumidity.getText().toString());
    allData.put(pData.ind_vars[7],maWeather.textPrecip.getText().toString());
    allData.put(pData.ind_vars[8],maWeather.textPressure.getText().toString());
    allData.put(pData.ind_vars[9],String.valueOf(maPlaces.bank.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[10],String.valueOf(maPlaces.bar.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[11],String.valueOf(maPlaces.beach.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[12],String.valueOf(maPlaces.bridge.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[13],String.valueOf(maPlaces.cemetery.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[14],String.valueOf(maPlaces.church.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[15],String.valueOf(maPlaces.clinic.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[16],String.valueOf(maPlaces.commercialBuilding.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[17],String.valueOf(maPlaces.communityCenter.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[18],String.valueOf(maPlaces.convenienceStore.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[19],String.valueOf(maPlaces.fireStation.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[20],String.valueOf(maPlaces.gasStation.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[21],String.valueOf(maPlaces.governmentOffice.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[22],String.valueOf(maPlaces.greenField.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[23],String.valueOf(maPlaces.hospital.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[24],String.valueOf(maPlaces.hotel.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[25],String.valueOf(maPlaces.highway.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[26],String.valueOf(maPlaces.highwayPedestrian.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[27],String.valueOf(maPlaces.highwayPrimary.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[28],String.valueOf(maPlaces.highwaySecondary.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[29],String.valueOf(maPlaces.highwayTertiary.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[30],String.valueOf(maPlaces.highwayResidential.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[31],String.valueOf(maPlaces.industrialBuilding.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[32],String.valueOf(maPlaces.mall.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[33],String.valueOf(maPlaces.marketplace.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[34],String.valueOf(maPlaces.park.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[35],String.valueOf(maPlaces.parkingArea.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[36],String.valueOf(maPlaces.pawnshop.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[37],String.valueOf(maPlaces.pharmacy.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[38],String.valueOf(maPlaces.policeStation.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[39],String.valueOf(maPlaces.postOffice.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[40],String.valueOf(maPlaces.privateOffice.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[41],String.valueOf(maPlaces.recreationalArea.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[42],String.valueOf(maPlaces.road.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[43],String.valueOf(maPlaces.residentialBuilding.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[44],String.valueOf(maPlaces.restaurant.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[45],String.valueOf(maPlaces.school.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[46],String.valueOf(maPlaces.sportsField.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[47],String.valueOf(maPlaces.touristSpot.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[48],String.valueOf(maPlaces.transportTerminal.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[49],maEconomy.textPHPUSD.getText().toString());
    allData.put(pData.ind_vars[50],maEconomy.textPSEI.getText().toString());
    allData.put(pData.ind_vars[110],maEconomy.textCPIAll.getText().toString());
    allData.put(pData.ind_vars[111],maEconomy.textCPIAlcohol.getText().toString());
    allData.put(pData.ind_vars[112],maEconomy.textCPITransport.getText().toString());
    allData.put(pData.ind_vars[113],maEconomy.textCPIHousing.getText().toString());
```

```
    allData.put(pData.ind_vars[114],maEconomy.textCPIRestaurant.getText().toString());
    allData.put(pData.ind_vars[115],maEconomy.textRateInflation.getText().toString());
    allData.put(pData.ind_vars[116],maEconomy.textRateSavings.getText().toString());
    allData.put(pData.ind_vars[117],maEconomy.textRateBank.getText().toString());
    allData.put(pData.ind_vars[118],String.valueOf(maTimeDayWeek.timeAfterMidnight.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[119],String.valueOf(maTimeDayWeek.timeAfterWorkHours.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[120],String.valueOf(maTimeDayWeek.timeAfternoon.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[121],String.valueOf(maTimeDayWeek.timeEarlyMorning.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[122],String.valueOf(maTimeDayWeek.timeEvening.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[123],String.valueOf(maTimeDayWeek.timeMorning.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[124],String.valueOf(maTimeDayWeek.dayFri.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[125],String.valueOf(maTimeDayWeek.dayMon.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[126],String.valueOf(maTimeDayWeek.daySat.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[127],String.valueOf(maTimeDayWeek.daySun.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[128],String.valueOf(maTimeDayWeek.dayThu.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[129],String.valueOf(maTimeDayWeek.dayTue.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[130],String.valueOf(maTimeDayWeek.dayWed.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[131],String.valueOf(maWeather.weatherClear.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[132],String.valueOf(maWeather.weatherCloudy.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[133],String.valueOf(maWeather.weatherRainy.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[134],String.valueOf(maTimeDayWeek.stayDay.isChecked() ? 1 : 0));
    allData.put(pData.ind_vars[135],String.valueOf(maTimeDayWeek.stayNight.isChecked() ? 1 : 0));

    return isValid;

}
```