Evaluation of Vulnerability Status of the Infection Risk to COVID-19 using Geographic Information Systems and Multi-Criteria Decision Analysis: A case study Addis Ababa City, Ethiopia.

By: Hizkel Asfaw Worku

A Thesis Submitted to
The department of Geomatics Engineering
School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Geoinformatics Engineering

Office of Graduate Studies
Adama Science and Technology University

July, 2021
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Advisor: Tilahun Erduno (Ph.D.)

Co-Advisor: Shankar Karuppannan (Ph.D.)

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APPROVAL SHEET

We, the advisors of the thesis entitled "Evaluation of Vulnerability Status of the Infection Risk to COVID-19 using Geographic Information Systems and Multi-Criteria Decision Analysis: A case study Addis Ababa City, Ethiopia." And developed by Hizkel Asfaw Worku, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date
Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Hizkel Asfaw Worku have read and evaluated the thesis entitled "Evaluation of Vulnerability Status of the Infection Risk to COVID-19 using Geographic Information Systems and Multi-Criteria Decision Analysis: A case study Addis Ababa City, Ethiopia." and examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics Engineering.

Chairperson	Signature	Date
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External Examiner	Signature	Date

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head	Signature	Date
School Dean	Signature	Date
Office of Postgraduate Studies, Dean	Signature	Date

DECLARATION

I hereby declare that this Master Thesis entitled "Evaluation of Vulnerability Status of the Infection Risk to COVID-19 using Geographic Information Systems and Multi-Criteria Decision Analysis: A case study Addis Ababa City, Ethiopia." is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Hizkel Asfaw Worku	______________________	_______________
Name of the Student	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled "Evaluation of Vulnerability Status of the Infection Risk to COVID-19 using Geographic Information Systems and Multi-Criteria Decision Analysis: A case study Addis Ababa City, Ethiopia." prepared under our guidance by Hizkel Asfaw Worku submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Geoinformatics Engineering. Therefore, we recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Tilahun Erduno (Ph.D.)	____________________	____________________
Major Advisor	Signature	Date
Shankar Karuppannan (Ph.D.)	____________________	____________________
Co-advisor	Signature	Date

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LIST OF ACRONYMS

AAHB	Addis Ababa Health Bureau
AHP	Analytical Hierarchical Process
AIDS	Acquired Immune Deficiency Syndrome
AU	African Union
CFR	Case Fatality Rate
COVID-19	Corona Virus Disease 2019
CSA	Central Statistical Agency
EPHI	Ethiopia Public Health Institute
ETB	Ethiopian Birr
FMoH	Federal Ministry of Health
GDP	Gross Domestic Product
GIS	Geographic Information System
GMT	Greenwich Mean Time
GPS	Global Positioning System
HIV	Human Immunodeficiency Virus
ICU	Intensive Care Unit
MCDA	Multi-Criteria Decision Analysis
MCE	Multi-Criteria Evaluation
MERS-CoV	Middle Eastern Respiratory Syndrome Coronavirus
NCGIA	National Center for Geographic Information and Analysis
RT-PCR	Reverse transcription-polymerase chain reaction
SARS-CoV	Severe Acute Respiratory Syndrome Coronavirus
SSA	Sub-Saharan Africa
UN	United Nation
UNECA	United Nations Economic Commission for Africa
USD	United State Dollar
UTC	Universal Time Coordinated
WHO	World Health Organization

ABSTRACT

COVID-19 is a disease caused by a new coronavirus called SARS-CoV-2 and is an accidental global public health threat. Due to this WHO declared the COVID-19 outbreak a pandemic. The pandemic is spreading unprecedently in Addis Ababa, which results in extraordinary logistical and management challenges in response to the novel coronavirus in the city. Thus, management strategies and resource allocation need a vulnerability-oriented approach. Though various studies have carried on Covid-19, Only a few studies on vulnerability from a geospatial/location-based perspective are conducted but at wider spatial resolution. This puts the result of those studies under question while their findings projected to the finer spatial resolution. To overcome these problems, the integrations of Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA) are developed as a framework to evaluate and map the susceptibility status of the infection risk to Covid-19. To achieve the objective of the study, following data such as Landuse, Population density, distance from roads, distance from hospitals, distance from bus stations/terminals, distance from the bank, distance to Markets, number of people with COVID-19, distance to health care unite, and distance to government offices are used. The criteria population density, number of COVID-19 cases, and landuse rasterized and reclassified to make them suitable for further analysis. The rest criteria are analyzed through proximity analysis and reclassified into vulnerability mode. The weighted overlay method was used; to evaluate and map the susceptibility status of the infection risk to the Covid-19. The result showed that out of the total study area, 32.62% (169.91 km^2) fall under Low vulnerable (1), and the area which covers 40.9% (213.04 km^2) is under moderate vulnerable class (2) for infection risk of COVID-19. The highly vulnerable (3) covers an area of 25.31% (132.85 km^2), and the remaining 1.17% (6.12 km^2) is under an extremely high vulnerable class (4). Thus, pandemic control mechanisms like disinfection could be addressed regularly to these priority zones. The health sector, local governments, the scientific community, and the population, in general, will use the result of this study as a useful tool to better understand where the pandemic transmission center and identify areas where more protective measures and response actions need to be in place at finer spatial resolution.

Keywords: COVID-19, GIS, MCDA, Proximity analysis, weighted overlay.

CHAPTER I: INTRODUCTION

1.1. Background of the Study

COVID-19 is a disease caused by the SARS-CoV-2, which is a new coronavirus (WHO, 2020). COVID-19 is an unintended global public health threat, especially for countries with limited resources. The disease was first identified on December 31, 2019, in Wuhan, China, and has since spread throughout the world(Hui et al., 2020).The World Health Organization (WHO) called the COVID-19 outbreak a pandemic due to the dramatic rise in the number of cases worldwide (WHO,2020). Coronavirus disease 2019 (COVID-19) is a contagious respiratory disease caused by a new coronavirus species that cause serious clinical symptoms such as fever, dry cough, dyspnea, respiratory problems, and pneumonia. It can lead to respiratory failure and death (Coccia, 2020). The disease is transmitted from person to person by contaminated air droplets that are ejected through sneezing or coughing. Humans who come into contact with virus-infected hands or surfaces and then touch their eyes, nose, or mouth with those hands may also spread the disease (Africa CDC,2020).

COVID-19 is a virus that affects people of all ages. However, proof to date indicates the elderly (i.e., over 60); and those with an underlying illness(such as heart disease, diabetes, chronic respiratory disease, and cancer) are more likely to contract the serious COVID-19 disease (WHO,2020). Ethiopia is one of the most populated countries in Sub-Saharan Africa, with a population of around 115 million people. It is also one of the poorest nations, with a per capita income of 850 dollars in 2019 and a human development index of 0.47, ranking 173rd out of 189 countries and territories. The country's major health concerns are tuberculosis (TB), malaria, Human Immunodeficiency Viral Infection and (HIV/AIDS), and maternal mortality, and it is one of the countries with the highest rates of TB, TB/HIV, and multidrug-resistant TB (Mohammed et al., 2020).

The first confirmed case of COVID-19 in Ethiopia was on March 13, 2020. As of November 11, 2020, 104,427 cases had been reported positive, with 1607 (case fatality rate, CFR = 1.5%) deaths and 64,983 (62.2%) recoveries. The primary case was a 48-year Japanese man, and consequently, the second report was three cases, one Ethiopian and two Japanese, who had contact with the primary case. In the capital Addis Ababa, which is a busy center of economic, social, and political activity and home to such prominent offices as the AU, reported the first two cases of COVID-19 on March 29, 2020, both having a travel history to Dubai at different dates (Lia,2020). The cases were mostly imported and sourced from mandatory quarantines before community transmission started. Until June 2, 2020, 30.4 percent of all cases had been imported, indicating that the disease was contracted outside of the country. The majority of the incidents, 5337 (98.4%), included Ethiopian nationals from all nine National Regional States and two City Administrations. Throughout the country, most of the cases 3822 (71.6%) had been reported from Addis Ababa (Mohammed et al., 2020).

Following the first case of COVID-19 in Ethiopia in March 2020, the Ethiopian government took several public health actions to halt the pandemic's spread. On March 30, 2020, the Prime Minister called on the public to have more discipline in fighting the coronavirus's spread in the country and appealed to the public to fulfill their responsibilities by applying all recommended prevention measures. On April 8-10, 2020, the government and parliament proclaimed a state of emergency, and on April 11, 2020, the council of ministers released a regulation. The National Ministerial Committee emphasizes, among other things, prevention and protection; a 14-day mandatory quarantine for passengers arriving in Ethiopia, avoiding public/religious assemblies; health sector capacity building; and market regulation to avoid unethical exploitation of the situation; and support regions' preparedness to forestall the disease (office of Prime Minister, 2020). Similarly, the emergency declarations and regulations stress avoiding handshakes, reducing the number of people using public transportation by half, maintaining sufficient physical distance, providing cleaning and handwashing facilities in a different part of each city (Baye, 2020).

Although the above-mentioned measure had taken, the number of COVID-19 infections has grown rapidly. Till Nov 1, 2020, the growth was with an incidence rate of 650 cases per 10,000 tests at the national level. This amount rises to 674 cases per 10,000 tests since Dec 1, 2020. This suggests the rate increased by 27 more cases countrywide in the only one-month interval (EPHI,2020). While in Addis Ababa, the incidence rate was 805 cases per 10,000 tests till Nov 1, 2020. This number escalated to 835 since Dec 1, 2020, incremented by 30 cases from that of Nov 1, 2020 (AAHB,2020). Until Dec,1,2020 total cases of 96583 were recorded in the country and 58,853 cases in Addis Ababa. This indicated that above 50% of cases in the counties are recorded in Addis Ababa.

The above-mentioned fact implies that the pandemic is spreading at a fast rate in the city. Besides, the government has loosened restrictions on social services, religious assemblies, markets, and other suggested pandemic-prevention measures (Biadgilign & Yigzaw, 2020). These conditions are conducive to pandemic spread and will greatly accelerate

COVID-19 expansion in the upcoming months. It is then indispensable for the government and concerned body to have operative methodologies to help the local pandemic prevention mechanisms by strengthen decision-making in order to mitigate and control COVID-19's spread.

Various researchers have implemented Multiple Criteria Decision Analysis (MCDA) techniques integrated with the Geographic Information System to evaluate vulnerability to infection risk and contagion control (Sánchez et al., 2020; Qayum et al., 2015; Ahmad et al., 2017). These two distinctive disciplines, GIS and MCDA, can benefit from each other. According to Martel & Chakhar (2003), GIS has many weaknesses in the domain of spatial decision-making. Integration of GIS technology with MCDA is the solution to these limitations. Moreover, Malczewski(2006) indicates that MCDA provides a comprehensive set of tools and approaches for organizing decision-making problems and designing, assessing, and ranking possible alternatives. Besides, Cowen (1990) found that GIS techniques and procedures play an important role in the analysis of decision problems. GIS is also known as a decision-making process that involves the incorporation of spatially referenced data into a problem-solving context. Therefore Malczewski(2006) concluded as, GIS-MCDA, at its most basic level, is a tool for transforming and combining geographic data with value judgments (the decision-maker's preferences) to acquire information for decision making. Thus, this brings various favorable circumstances to practice for public health planning and epidemiological studies. Through monitoring the source of disease and the spread of contagion, agencies may respond more efficiently to disease outbreaks by identifying a population at-risk and targeting action.

Vulnerability is defined as "the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards" (Heylin, 1986), is defined in this study as the people's susceptibility to the infection risk of COVID-19 epidemic. However, different MCDA techniques are used for vulnerability assessment, the Hierarchical Analytical Process (AHP) is one of the most commonly used approaches in decision-making processes, initially developed by Saaty (1980). The reason for its implementation is that it allows the relative value of two or more attributes to be evaluated by pairwise comparisons (Ng, 2016). It is capable of taking into account all factors in a hierarchical style usually based on the perception of the person, which enables these factors to be systematically organized and their contribution to the risks to be explained with priority weights. It is commonly used since the result is simple to understand, interpret, and implement. AHP is particularly useful for addressing both qualitative and quantitative multi-criteria factors in the decision-making process(Chen et al., 2018).

Geographical Information Systems (GIS) are now well established both as a technology and a set of tools for manipulating and displaying spatial data in an ever-increasing range of application areas (Garner et al., 2014). Over the last few decades, the increased use of Geographic Information System technology has changed health care services and provided new insight to public health providers, researchers, hospital and health system staff, as well as the public they serve. Though maps and spatial analysis have a long history of health and human services, the early twenty-first century is a period when health practitioners and the general public have access to a wealth of powerful spatial analytic tools (Davenhall & Kinabrew, 1970).

Through vulnerability and risk analysis, spatial prediction, tracking spatial resource distributions, and providing spatial logistics for management, geographic information systems (GISs) have played a significant part in providing significant insight during previous virus outbreaks such as Zika, influenza, West Nile, Dengue, Chikungunya, Ebola, Marburg, and Nipah (Zhou et al., 2020).

This study aims to evaluate the vulnerability status of infection risk to the COVID-19 pandemic in Addis Ababa city, Ethiopia, by standardizing and putting a vulnerability model into operation, using Geographic Information Systems (GIS) and Multi-Decision Criteria Analysis (MCDA). Since identifying vulnerable areas to infection risk of COVID-19 pandemic have an evitable role in implementing intended infection prevention and control actions to tackle the significant causative factors at their specific locations. Spatial analysis with GIS, on the other hand, can illustrate the human and ecological environment during which diseases are transmitted to spot susceptibility and possible intervention and it can be used to detect a group of diseases and the proximity of vulnerable population to the risk source (WHO,2020). It is anticipated that the results of this study will provide valuable scientific knowledge to decision-makers about how to use GIS tools to take steps to control and monitor the pandemics and serve as a benchmark for application in other cities or areas.

1.2. A Statement of the Problem

Recently COVID 19 has become a global health burden for almost all countries in the world irrespective of their economic, social, political, and technological advancement. Its effects are linked with the health of humankind and the socio-economic, political, and environmental welfare of the globe. These effects are highly worse in Sub-Saharan Africa, where the healthcare system is vulnerable to the disease and lacks adequate resources to manage severe cases.

Despite various measures have taken, Addis Ababa is reeling from the coronavirus's unprecedented spread with a faster rate of expansion. Data by the city's health bureau suggests that the number of COVID-19 cases was low in the first 50 days after the index case was reported, with an average of three cases per day. However, the number escalated to 239 per day on average since Dec 1, 2020, within 247 days after the first case was reported (AAHB,2020), which indicates that the case is sharply increasing. Thus, patient intake capacities of isolation and treatment sites become to attain their maximum, and the management system is getting challenged. According to FMoH(2020), the number of patients in need of intensive care is increasing (especially in Addis Ababa) beyond the capacity of health facilities. On average, 305 patients who are admitted to the treatment center for COVID-19 every day are in the intensive care unit, 40 to 45 of whom use a Mechanical Ventilator. So far, 59 percent of those admitted to the intensive care unit have died, according to the report on the official Facebook page. The figure is expected to be intensified in the upcoming months due to multiple factors such as the great negligence and inattention observed in society; the Low-risk perception and the lack of each stakeholder's role are cited as the main reasons (FMoH,2020). These led to extreme frustrations in the health professionals who are front liners in combating the pandemic and improper allocation of scarce resources. Thus, management strategies and resource allocation need a vulnerability-oriented approach.

Though researchers have carried various studies on COVID-19, most of the studies are focus on the distribution and transmission pattern of the COVID-19 pandemic (Begashaw and Yohannes, 2020; Ranjan, 2020; Gebremariam et al., 2020). However, less attention has been placed on location-based vulnerability statutes to decrease the spread of disease. Emerging research has begun to evaluate the social vulnerability to COVID-19 and its socioeconomic effects at the country level, both in incidence and outcome (Girum Abebe, 2020; Alessandra, 2020; Ethiopia, 2020).

Only a few studies on vulnerability from a geospatial/location-based perspective have been conducted. The studies have focused on the worldwide or national level, with a lesser focus on finer spatial resolutions such as regional or city-level (Addis Alene et al., 2021). This puts the result of those studies under question while their findings are projected to the finer spatial resolution.

Hence, this study evaluates the Vulnerability status to infection risk of COVID-19 within the study area to better understand where the pandemic transmission center and identify areas that need more preventive measures and response actions at finer spatial resolution.

1.3. Research Objectives

1.3.1. General Objective

The general objective of this study is to evaluate the vulnerability status of infection risk to COVID-19 in Addis Ababa City with the application of the Multi-Criteria Evaluation (MCE) Technique in the GIS environment.

1.3.2. Specific Objectives

The Specific objectives of the study are to:

i. identify appropriate effective factors to evaluate the susceptibility status of infection risk to the COVID-19 pandemic in the study area.

ii. to show the integration of Multicriteria Evaluation Technique (MCDA) and Geographic Information System (GIS) to evaluate vulnerability statuses of infection risk to COVID-19.

iii. map an area in terms of vulnerability status of infection risk to COVID-19.

iv. locate extremely high vulnerable areas for infection risk of COVID-19 in the study area.

1.4. Research Question

i. What are significant factors to evaluate COVID-19 infection risk susceptibility status?

ii. How do the multicriteria evaluation technique (MCDA) and Geographic Information System (GIS) are integrated to evaluate the vulnerability status of infection risk to COVID-19?

iii. What percentage of an area in Addis Ababa is highly vulnerable to infection risk of COVID-19 pandemic?

iv. Where is extremely high vulnerable area in Addis Ababa in terms of the vulnerability status of COVID-19 infection risk?

1.5. The Significance of the Study

Identifying the spatial vulnerability status particularly, the hotspot location in terms of vulnerability status of infection risk of COVID-19 with their magnitudes, can be used as the basic information for preventing resource wastage by allocating resources in high priority areas. If the critical areas with the highest vulnerability status will be identified, the pandemic combating measures could be smooth through its implementation. The findings of the study are used as a basis to provide more detailed location-based information about the vulnerability of an area to infection risk of COVID-19 in the city, the clue for a further investigation aimed at addressing the evaluation of the vulnerability status of contagion risk to a different pandemic.

Finally, the society and different stakeholders such as policymakers, health officials, and health experts get the following benefits: It provides important scientific information on the use of GIS tools to take action to prevent the pandemic and control measures for decision-makers, especially for the health sector. The finding in this study is simply transferable to other cities or regions and can be extended to the national level for decision-making on an immediate or long-standing basis towards planning, decision-making, and prioritization of areas for targeted control interventions. The resulting vulnerability status map is based on administrative boundaries convenient for the health officials and stakeholders for formulating remedial strategy. It also helps as input for the government and other concerned bodies for their decision-making processes related to COVID-19 spread control.

1.6. Scope of the Study

This study focuses on the evaluation and mapping of susceptibility statuses of contagion risk to the COVID-19 pandemic using the method of GIS-MCDA. It carried from February to June 2021. The area coverage of this study is limited to Addis Ababa City's administrative location.

1.7. Limitation of the study

There are some drawbacks to this study that could be addressed in future studies in the field. Limited data access for the criteria hospitals and lower clinics was one of the big drawbacks; it incurred some inaccuracy in the result. The other shortcoming was that instead of using general standards, the criteria of vulnerability status of COVID-19 infection risk was determined by analyzing various literature and previous knowledge in the field.

1.8. Organization of the research project

There are five chapters to the research project. The background of the study, a statement of the problem, objectives, research questions, significance of the study, scope, and limitations of the study are all presented in the first chapter. The theoretical and empirical literature are reviewed in the second chapter. The third chapter describes the study area and details the methodology. The study's findings are presented and discussed in Chapter four. The conclusion and recommendations are presented in the final chapter.

CHAPTER II: LITERATURE REVIEW

2.1. Theoretical framework

2.1.1 Some concepts of COVID-19 and its Behavior

Epidemics and pandemics have marked human history since time immemorial. Over the last decades, coronaviruses outbreaks such as the SARS CoV outbreak in 2002 and MERS-CoV in 2012 have placed global public health institutions on high alert (Unhale et al., 2020). Novel coronavirus disease 2019 (Covid-19) is a global pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). According to WHO Novel coronavirus disease, 2019(COVID-19) is one among a large family of coronaviruses that can infect birds and mammals, including humans. The disease was first identified in December 2019 in Wuhan, China, and has since spread across the world, declared as the world pandemic. Fever, cough, and shortness of breath are all common symptoms. Other signs include muscle pain, sputum production, diarrhea, sore throat, loss of smell, and stomach pain. While the majority of cases lead to mild symptoms, there has been some progress in the fight against viral pneumonia and multiorgan failure (Guan et al., 2020).

The virus spreads mostly during close contact, created from small droplets when individuals cough, sneeze or speak. While respiratory droplets may be formed during respiration, the virus is normally not airborne (WHO,2020). By touching a contaminated surface and then their faces, people can also contract COVID-19. When people are symptomatic, it is most infectious, while propagation can be possible before symptoms occur. The virus can survive on surfaces for up to 72 hours (van Doremalen et al., 2020). In general, it takes two to fourteen days from contact to the inception of symptoms, with an average of five days. The reverse transcription-polymerase chain reaction (RT-PCR) from a Nasopharyngeal swab is the normal method of diagnosis (Wang et al., 2020). Regular hand washing, social distancing (keeping a physical distance from others, especially those with symptoms), concealing coughs and sneezes with a tissue or the inside elbow, and keeping dirty hands away from the face are all recommended infections prevention methods. Masks are recommended for persons who believe they have the virus and they are caregivers. The general public's perceptions on mask use vary, with some authorities advising against them, others encouraging them, and still others mandating them. COVID-19 is currently without vaccination or particular antiviral medication. Treatment requires symptom management, compassionate care, isolation, and experimental approaches (WHO,2020).

2.1.2 Global COVID-19 Epidemiology and Burden

Currently, the planet is at an alarming pace of infection with COVID-19 and is on an uncharted pathway. WHO Coronavirus Disease (COVID-19) Dashboard as of 03:26 UTC, 13 December 2020, reported that confirmed cases were raised in 71,649,876 with total global deaths and recoveries standing 1,604,516 and 46,811,784 respectively. Globally, the total number of active cases puts up at 23,233,576. At present, America has become a very heavily impacted nation in the world. Africa has been hit by the global epidemic, although infection rates are projected to be lower than in other parts of the world (WHO,2020). Nevertheless, as at 13/12/2020, 10:00 GMT, Africa reported 2,361,271 cumulated cases (3.30 % global share), 55,989 deaths (3.49 % global share) and 2,004,985 recoveries (4.28% global share) (AfricanCDC,2020). Almost every African country has been affected by COVID-19.

2.1.3 COVID-19 in Ethiopia

Ethiopia is a developing country in the sub-Saharan African region, facing a twofold burden of infectious and non-infectious diseases (Misganaw et al., 2017). Also, the ongoing pandemic of COVID-19 brings further frustration to the country's health system and the country as a whole. Several measures have been taken by the Government of Ethiopia to deal with the pandemic earlier than the first case detection and are still being updated accordingly. These include health infrastructure capacity building, establishing a task force in different levels that will lead the control and prevention process of the disease, proclaiming the state of emergency, awareness creation via different methods, preparing COVID-19 isolation and quarantine centers, and resource mobilization to support groups at-risk and others. Unfortunately, while various measures are implemented, the number of cases continues to rise, and an exponential increase is anticipated in the upcoming months (FMoH,2020).

2.1.4 Challenges Related to COVID-19 in Ethiopia

It is noticeable that COVID-19 adds more stress to the country's health system. This would complicate things for nations like Ethiopia, whose health systems do not offer basic and consistent health care to their people under regular conditions. On all metrics, the institutional capacity of the Ethiopian Health Institution is low, even contrasted to the average of Sub-Saharan Africa (SSA). For example, in 2017, Ethiopia's national general government health expenditure per capita was more than half (24.95), lower than the SSA average (69.19) (World Bank,2018). The lack of medical professionals, both in terms of quantity and quality, is also a significant challenge. Regarding the quantity, according to

WHO, the proportion of health professionals to the population in Ethiopia is 0.96 per 1000 people (Haileamlak, 2018). This is far below the WHO's suggested standard (4.45 per 1000 people) for meeting the health targets of the Sustainable Development Goals (WHO,2016). This shows that the country's health needs are not being adequately addressed, and the addition of unexpected COVID-19 related needs is worsening the problem.

Another unfortunate situation is that the health workers, who are regarded as the pillars of the health care systems are among the COVID-19 high-risk groups (Ng K et al., 2020), if they are infected significantly with coronavirus, the health system can subside. Ethiopia's non-human capitals are also insufficient in terms of both quality and quantity. The health facilities are fewer in number, and they are not properly equipped. For a population of 110 million people, Ethiopia currently has just 557 mechanical ventilators and 570 intensive care unit (ICU) beds(Shigute et al., 2020); Wamai, 2009). Frequent hand washing is one of the most effective ways to prevent COVID-19 transmission (WHO,2020), yet 43 percent of Ethiopia's rural population lacks access to a reliable source of clean water, thus, regular handwashing practice is ideal (CSA,2016).

On the other hand, homelessness and overpopulation are also problems in response to coronavirus in Ethiopia. As per WHO Health and Housing Guidelines, Crowded housing conditions are among the high-risk areas of infection for all inhabitants (WHO,2018). According to a survey in 11 Ethiopian cities, the number of people living in the streets has reached around 88 thousand. The study also suggests that many of the homeless are living in the state capitals. Of the 88 thousand homeless, infants, women, youth, and the elderly make up the bulk of the population (Tamire, 2019). The Ethiopian population that is homeless or uninhibited raises the risk of infection of COVID-19 distributed throughout the group. Then again, One of the most distinctive characteristics of Ethiopian society is its vibrant social life (Duguma & Hager, 2011). Ethiopians practice a spiritual and communal life. Warm greetings, handshakes, positive body language, kissing on the cheek, and hugging are part of the normal greetings. Praying together, bowing in front of a priest is commonly practiced. However, the disease's infectious nature prohibits people from suchlike practices, and Cultural values have been highly challenged.

2.1.5 MCDA and GIS in Infection risk vulnerability Evaluation and Mapping

Multi-criteria decision analysis (MCDA) is a decision support method that enables different quantitative and qualitative criteria to be considered using data-driven and qualitative stakeholder involvement measures. In the field of operational research, multi-criteria decision analysis has been initiated and subsequently extended to various fields, including ecology, agriculture, transport, city planning, and public health (Marsh et al., 2018; Elsheikh et al., 2015; Eniyew, 2018). The decision analysis of multi-criteria employs statistical methods and human intuition, facilitates expert engagement, and takes into account nonlinear interactions that are normal between disease and ecology. In the assessment of disease risk, multi-criteria decision analysis often enables the combining of several ecological variables through decision rules generated from current information or postulated understanding of the criteria, directing to the incidence of diseases(Hongoh et al., 2011; Cox et al., 2013).

Geographic information systems have been popularly implemented in disease risk vulnerability evaluation and mapping. In combination with MCDA, GIS-MCDA could support in gaining understandings into program management's impact in public health and other contexts of spatial restraints such as zoning, landuse, or demography (Abdul Rasam et al., 2019; Kassaw et al., 2019). The GIS-MCDA model benefits from being an evidence justification approach that provides a formal framework for sharing of knowledge between the various stakeholders and reduces the problem's unstructured nature. It can also help the decision-making process enhancement and validation (David, 2015). The GIS-MCDA has been shown to provide a systematic and complete approach to evaluating and mapping COVID-19 susceptibility (Sánchez et al., 2020).

2.1.6 Global experience in Using GIS for pandemic mitigation and control

The magnitude of 'where' takes on more importance than 'who' and 'when' in the event of an outbreak. In epidemiology, geospatial resources and data have enormous potential; mapping the case, collecting sufficient supplementary data, and making evidence-based decisions. Geospatial information can be used in the battle against an outbreak to help policymakers make smart decisions through staff monitoring, verified case spreading, network management, and spatial data analysis. “When combined with Big Data, geospatial data can play a positive role in rapid visualization, dissemination of epidemic information, spatial tracing of virus source, prediction of regional spread, risk division of regions, identification of prevention and control priorities, control of resources and panic elimination,” said Super Map Technical Director. Although the continued loss of life and business due to the COVID-19 is both devastating and troubling, it is also an opportunity for decision-makers to recognize that geospatial technology and data are critical to prevent and respond to the spread of pandemics(Dhingra, 2020). the world experienced the use of GIS for pandemic mitigation and control in past decades, such as the Ebola virus, the Zika virus, and the Avian virus.

2.1.6.1 West African Ebola virus epidemic

In west Africa and other areas of the world, the three-year Ebola virus outbreak (2013-2016) caused chaos. "At the time, ArcGIS was used to understand and forecast the actions of disease transmission, as well as to enable responding agencies to determine precisely where, how, and when to deploy resources. Technology has allowed communities to support interactions with organizations and to work together more transparently so that they could get the assistance they needed to get to the right place more quickly," recalls Esri Founder and president Jack Dangermond. Aside from mapping, a spatial-temporal study was carried out to evaluate the domestic risk factors for Ebola in inaccessible and highly affected areas, and the epidemic’s spatial severity transmission models were created. Geospatial resources and data have not only enabled the authorities to fight the virus but have also facilitated rapid response and sound decision-making(Dhingra, 2020).

2.1.6.2 Zika virus epidemic

A massive Zika fever outbreak, which stemmed from the Zika virus in Brazil, spread to South and North America regions by the beginning of 2015 and also affected many islands in the Pacific and Southeast Asia (Lowe et al., 2018). Zika virus mapping helped researchers to identify parts of the globe where the mosquito could thrive and to cross-refer to census data for the results. It soon became apparent that Zika posed a great danger to pregnant women and that areas with a large population of expectant mothers were reported. Required measures for the protection and well-being of the disadvantaged portion of society have been taken in these regions. Eventually, the use of geospatial technologies in virus monitoring contributed to successful policy-making research and social awareness. To reduce the spread of the disease, inhabitants of the worst-hit areas were advised to use insecticides and larvicides, among other things(Dhingra, 2020).

2.1.6.3 Avian influenza

Between February 2013 and March 2015, cases of humans being infected with an avian influenza A(H7N9) virus were reported from mainland China (ECDC,2014). To recognize and fight the virus, researchers used the available data to track the spread of the virus and predict where it will be next. Mapping the virus has helped in recognizing some very useful facts, such as the reasons behind the spread of the virus(Dhingra, 2020). Mapping various layers of data provided a helpful way of explaining the spread and risk factors for influenza. Also, the predictive risk map of human infections in China based on modeling was useful in identifying areas where surveillance and preventive interventions were required.

There is a marked rise in the awareness and usage of GIS technology in public health. Public health officials & practitioners, including policymakers, statisticians, epidemiologists, state & district medical officers, increasingly embrace and use GIS. Some of its possible public health applications are: Determine the geographical distribution & variation of diseases, Analyze diseases' spatial & temporal patterns, Map populations at risk & stratify factors of risk, Document the health care needs of the community & assess resource allocations, Forest epidemics, Plan & target interventions, Monitor diseases & interventions over time, Manage the environment, materials, supplies & human resources for patient care, Monitor the utilization of health centers, Publish health information maps on the internet, locate the nearest health facility (Degife, 2009).

2.2. Empirical framework

Vulnerability is defined as “the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards” (Heylin, 1986). Vulnerability to COVID-19 due to various factors such as environmental, social, and economical has been studied in different parts of the world such as the united states (Ali et al., 2021), Mexico (Sánchez-Sánchez et al., 2020), India (Imdad et al., 2021), and (Tavares & Betti, 2020) in Brazil. According to (Kiaghadiid et al., 2020), Vulnerability studies can help with pandemic mitigation and control in various ways, including providing a better understanding of the medical access gap, matching community resources to community needs, identifying the next hotspot, prioritizing actions, and so on.

Currently, most countries around the world have begun to use geospatial technologies for COVID-19 combat. For example, China has made various geospatial applications to fight against COVID-19 (Kamel Boulos & Geraghty, 2020). Well-known among them are the use of drones for critical medical supplies (Huber, 2020), detection of outbreak source (Yu et al., 2020), disinfection (Kamel Boulos & Geraghty, 2020), and selection of suitable sites for the construction of health facilities (BBC News, 2020). This revealed that geospatial technologies are applicable in the fight against the global pandemic. Many Geospatial tools have been used in various endeavors, all of which contribute to efforts put in place to tackle the pandemic. The comprehensive related literature reviewed is summarized in table 2.1 below.

Table 2.1: Summary of Empirical Review

Author Name	Method	Purpose/Aim of the study
Pourghasemi et al., 2020	A Geographic Information System (GIS)-based machine learning algorithm (MLA), support vector machine (SVM)	• Analyze the risk factors of coronavirus outbreak. • Identify the areas having a high risk of infection. • Evaluate the behavior of infection.
Gilbert et al., 2020	Used the Infectious Disease Vulnerability Index method	• Evaluate the preparedness and vulnerability of African countries against their risk of importation of COVID-19.
Lakhani, 2020,	Spatial(Geographic Information system) and hot spot (Getis-Ord Gi*) statistics Method	• Identify the location of priority areas. • The travel time to essential health services and palliative medicine and hospital services Identification.
Imdad et al., 2021	Geographic Information System and Getis-Ord Gi ∗ statistic (Moran’s I values)	• Link air travel and COVID-19 cases. • Geographic trajectories of the COVID-19 outbreak and hotspot identification • COVID-19 potential outreach analysis

Kanga, 2020	A GIS-based multi-criteria risk reduction method	• Hypothesized different COVID-19 risk indices • Map the risk • Defined hazard and vulnerability components
Acharya & Porwal, 2020	A Percentile ranking method	• Observed similarities between vulnerability and the current concentration of COVID-19 cases at the state level. • Evaluate vulnerability based on vulnerability index.
Ali et al., 2021	Pearson's correlation analysis, Jaccard similarity analysis, and Logistic Regression Analysis	• It is aimed at assessing the vulnerability of the US at the county level to COVID-19 using the pandemic data from January to June of the year 2020.

CHAPTER III. MATERIALS AND METHODS

This section illustrates the data used to attain the study's objectives as well as how the analysis was carried out. The present section gives the steps followed in generating the results discussed in the result section.

3.1. Description of the study area

3.1.1. Location and Size

Addis Ababa is the capital city of Ethiopia and is located on latitude 90º 1' 48''North and longitude 38º 44' 24'' East. The city lies at the foot of Mount Entoto with an elevation of 2,355 meters above sea level and covers about 540 km^2. Addis Ababa hosts the headquarters of the African Union (AU) and the United Nations Economic Commission for Africa (UNECA). The city is divided into 10 sub-cities without newly added sub-city: Addis Ketema, Akaky Kaliti, Arada, Bole, Gullele, Kirkos, Kolfe Keranio, Lideta, Nifas Silk-Lafto, and Yeka (United Nations Environment Programme, 2018).

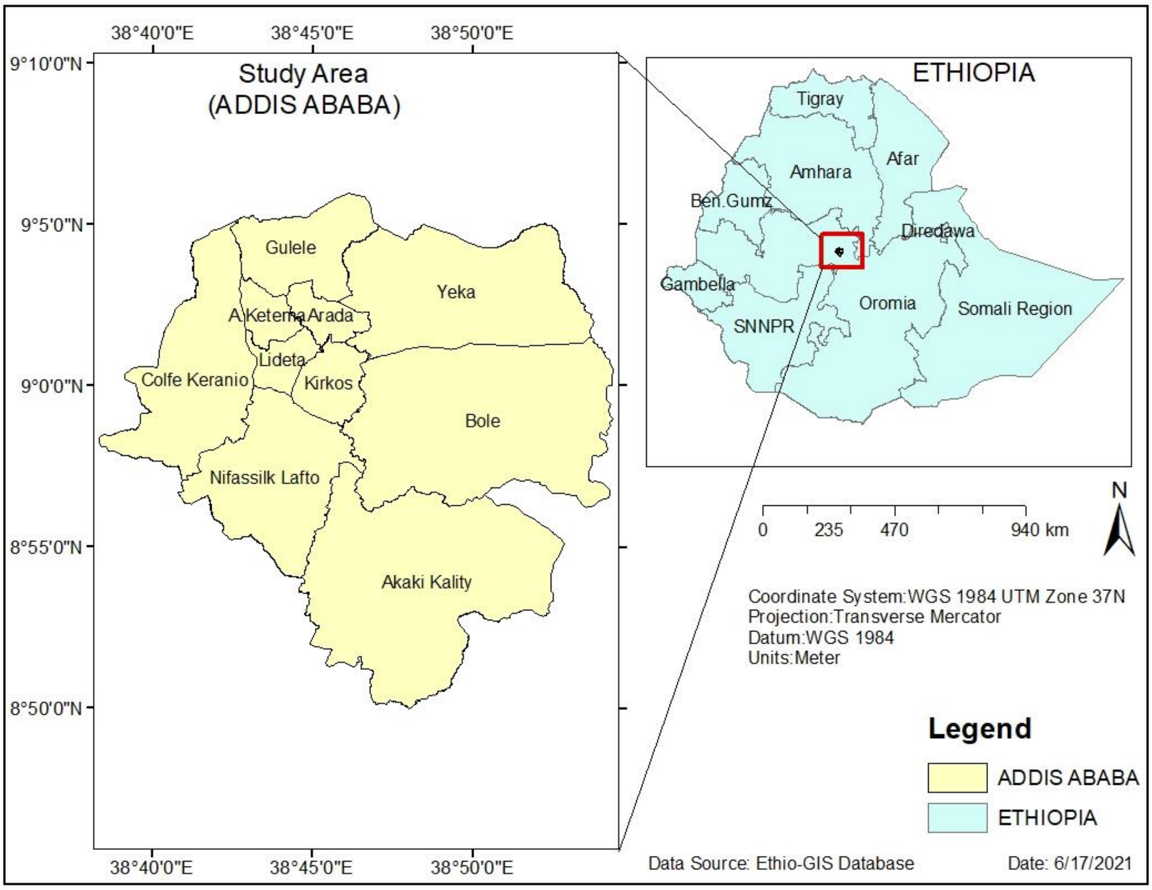

Figure 3.1: Location Map of the Study Area

3.1.2. Population

According to 2015 estimates by the Central Statistical Agency (CSA), the total population of Ethiopia was about 90 million. Addis Ababa is home to an estimated 3,434,000 inhabitants, which is 3.6% of the national population and 18% of the total urban population of Ethiopia. The city has a population density per square kilometer of 6,516 people. The population growth rate of Addis Ababa is around 2.1 percent per annum, with a projected population of 4.7 million people by 2030 (United Nations Environment Programme, 2018).

3.1.3. Climate and Topography

Addis Ababa lies between 2,200 and 2,500 meters above sea level. Addis Ababa encounters a humid subtropical warm summer climate due to its high altitude, which is mild with dry winters, mild rainy summers, and moderate seasonality. With an average annual temperature range of 10 ° C to 24 ° C. From February to May, the city has a short rainy season with a long wet season from June to mid-September (United Nations Environment Programme, 2018).

3.1.4. Socio-economic situations

The real GDP of Ethiopia grew by 8% in 2015/16, a decline from 10.4% in 2014/15, and is expected to remain stable at 8.1% in 2018. There is a GDP growth rate of around 14 percent in Addis Ababa. Ethiopian cities created approximately 227.3 billion Ethiopian Birrs, according to the State of Ethiopian Cities 2015 report (ETB). Addis Ababa's GDP was around ETB 66.3 billion in the same year, well above 29 percent of Ethiopian cities' total GDP. According to the city's Bureau of Finance and Economic Development survey, in 2016, Addis Ababa's per capita income rose from USD 788.48 in 2010 to USD 1,359 in 2015. The economy of Addis Ababa is mainly dominated by the services sector at 63 percent, followed by the industrial sector at 36 percent. In terms of employment, trade contributed 31 percent of the urban jobs, whereas the manufacturing sector accounted for 23 percent, community services 14 percent, and the construction sector 12 percent in 2015(UNhabitat, 2017). It is estimated that 22 percent of the population in Addis Ababa lives below the poverty line and that 29 percent of households are unemployed (higher than the national urban average of 15 percent) (CSA,2017).

3.1.5. Transport

Addis Ababa has made deliberate efforts over the past decade to improve the situation of urban transport, primarily through major investments in new infrastructure, including highways, a new Light Rail Transit (LRT) system, a new Bus Rapid Transit (BRT) system, and enhanced pedestrian infrastructure (World Bank, 2014). The city of Addis Ababa still lacks effective and affordable public transit networks, despite these changes. Increased demand for transport services is indicated by expanding the region, growing population sizes coupled with rapid economic growth. Public transport is projected to be used by 2.2 million people in Addis Ababa, with around 3.6 million daily trips to the city. City buses, minibuses, taxis, Light Rail Transit (LRT), and walking are the primary transport types in Addis Ababa. The prevalent modes are walking and animal carts in the suburbs. Public transport accounts for about 48 percent, while 9 percent and 43 percent respectively account for private cars and walking (Kebede & Odella, 2014).

3.2. Research Design

The conceptual structure or the design of the research project that the researcher followed in conducting the research is essential to clearly define and visualize the whole image of the work. Defining the research design highly contributes towards result findings by showing overall highlights of methods. Therefore, before the commencement of the research techniques, it is imperative to prepare tracks of the research by assembling all the requirements for the problem-solving objective (Fig. 3.2).

3.2.1 Approaches to the Research

In this study, both Quantitative and Qualitative research approaches are implemented to get the final result and it can be known as Mixed Approach. Even though the qualitative side has more weightage than the quantitative, it is difficult to attain the objective of the study without the involvement of both.

3.2.2. Research Type

It is known that there are different types of researches to be employed based on the goal (purpose), Type of data, Field of study, or the aim (objective) of the research. Therefore, this study is categorized under the applied research type. Because the result can be applied to solve real-world problems.

3.3. Materials and Data collection

3.3.1. Data Sources

Different data of primary and secondary sources were collected from field surveys, online sources, and respective institutions. They are summarized below in Table 3.1.

Table 3.1: Data Source

S. No	Data	Source	Data type
1	Addis Ababa City boundary	Urban planning office	Shapefile
2	Coordinate data	Google Earth and filed work	CSV
3	Population data	Central Statistical Agency (CSA) 2020 Projected.	Text
4	Addis Ababa City Master Plan	Addis Ababa City Municipality	Shapefile/CAD file

3.3.2. Material/Software

Different materials and software were used to do the overall works. They are summarized below in Table 3.2;

Table 3.2: Software to be used

No.	Material/software Name	Purpose
1	Handheld GPS	To collect coordinate of a point
2	ArcGIS 10.8	✓ For data analysis and mapping ✓ For Editing spatial data in arc Map and non-spatial data in arc catalog.
3	IDRISI Selva	To calculate the weight of each layer.
4	Google Earth	To visualize spatial features in the study area and to get coordinates points as well.
5	MS-Excel and MS-Word	Integrating attribute data and preparing a thesis report

3.3.3. Data Collection Methods

To achieve the objective of this study, primary data such as coordinate data for (Market, Bank, Hospital, Lower Clinic, Terminals, and Government offices were collected directly from the field by using a handheld GPS. Secondary data like population number data, number of COVID-19 positive cases, boundary data, and the city master plan for extracting landuse and road were used and obtained from the respective source. Additionally, previous reports and documents, journal articles, thesis, textbooks, and the internet were used as secondary data.

3.4. Conceptual framework

The theoretical framework presented a review of literature on various theories related to evaluating the vulnerability status of pandemic infection risk, particularly the COVID-19 pandemic. Different methods of evaluating vulnerability are also.

A literature review has shown that disasters and adverse health events such as epidemics and pandemics disproportionately affect populations with significantly higher impacts on the most vulnerable (Lakhani, 2020; Gilbert et al., 2020; Pourghasemi et al., 2020). Indeed, significant health, socioeconomic, demographic, and epidemiological disparities exist within the study area when individual determinants considered. However, little is known about the spatial variation and inequities of the vulnerability status to infection risk of COVID-19.

Vulnerability studies can be conducted using a variety of methods, including the Infectious Disease Vulnerability Index method (Gilbert et al., 2020) and Geographic Information System (GIS)-based machine learning algorithm (MLA), support vector machine (SVM) (Pourghasemi et al., 2020). The Infectious Disease Vulnerability Index method is usually made by conducting a comprehensive review of relevant literature to identify factors influencing infectious disease vulnerability and sum up the overall vulnerability score and rank based on the value to identify the vulnerable area (Moore et al., 2016). Besides, other vulnerability indexes such as the Social Vulnerability Index (SVI), Epidemiological Vulnerability Index (EVI), and the combination of two have been used to measure the vulnerability of the community to pandemics (Macharia et al., 2020). Logistic Regression Analysis can also be used to study the vulnerability phenomenon(Ali et al., 2021). However, the aforementioned methods have a shortcoming in terms of expert interaction in the vulnerability evaluation process and the accommodation of nonlinear relationships between disease species and the environment. The finding mentioned above and modeling gaps are addressed in this research using the GIS-MCDA model. The MCDA can greatly improve decision-making by combining statistical tools and human intuition. Incorporated with GIS, MCDA methods facilitate a systematic and comprehensive way to identify the vulnerability status of infection risk to the COVID-19 pandemic. The study first identifies the problem and selects relevant criteria, MCDA (AHP), and Spatial Analysis in ArcGIS. The final vulnerability status of infection risk to the COVID-19 map is generated next. The conceptual framework is presented graphically below to achieve the objectives and answer the research questions of this study. So, the following systematic steps which is involved in the flowchart shown in Figure 3.2 were conducted and performed.

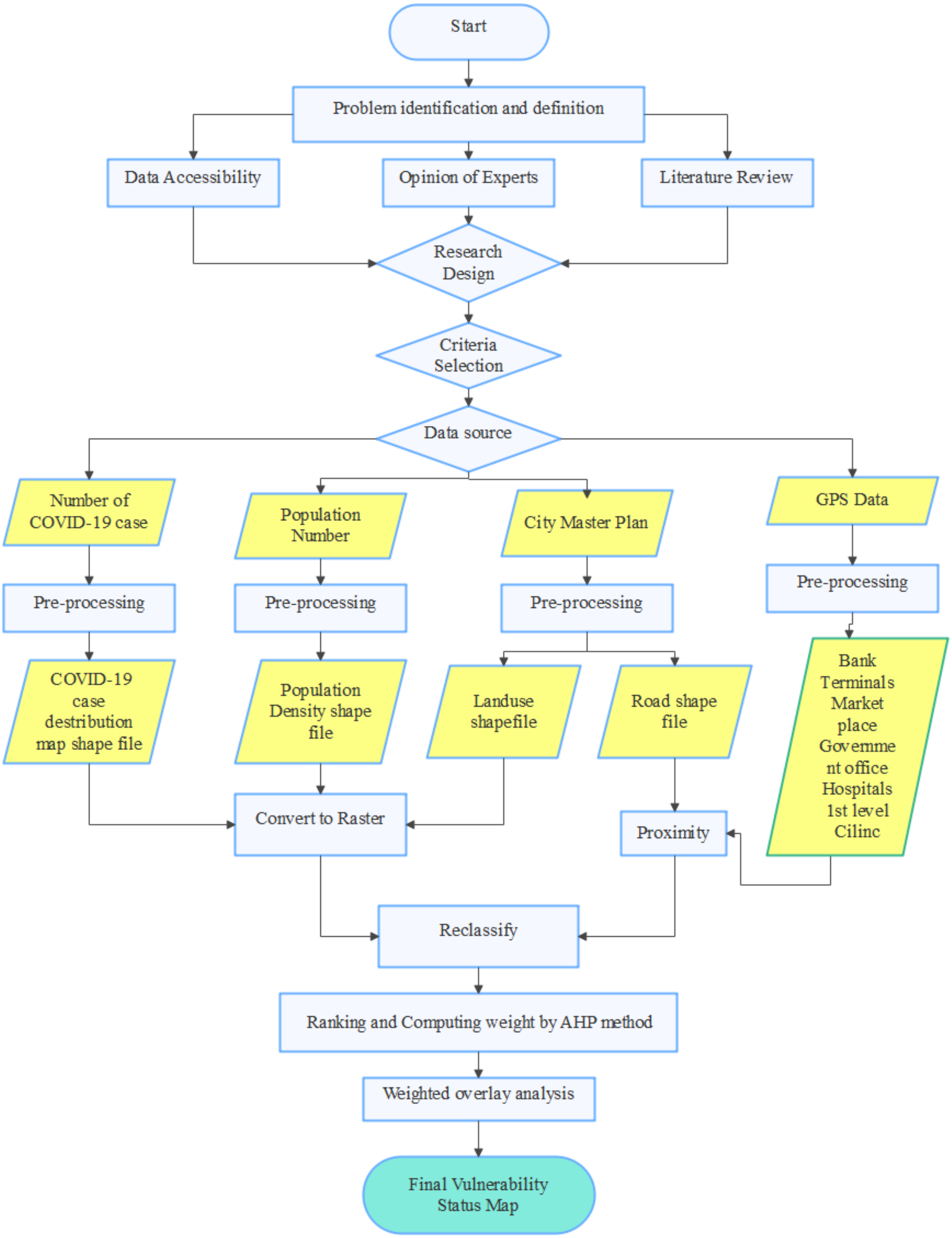

Figure 3.2. Conceptual framework flowchart of methodology adopted for the study

3.5. Method of Data Analysis

After the data was collected from various sources, the data were analyzed using different software like ArcGIS 10.8 and IDRISI Selva. The details of data analysis as per the conceptual framework flow chart presented in Figure 3.2 are discussed in detail in this section.

The primary step was to set the goal or define the problem and setting the research design. In this study, GIS-based MCDA aims to produce a map showing the vulnerability status of infection risk of COVID-19 in Addis Ababa city. The following step was determining factors/ criteria that are important for COVID-19 vulnerability status evaluation. It is important to choose the appropriate influential factors as their quality affects the validity of the results (Bui et al., 2019). Since no previous studies of the vulnerability status of an area to COVID-19 infection risk have been conducted, the selection of influential factors is a very challenging task. Besides, there are also no universal factors accepted for mapping and evaluating the vulnerability status of COVID-19 infection risk. In such circumstances, vulnerability factors can be identified by either collecting data from a literature review and prior knowledge of the phenomena. Ongoing research on pandemics has shown that local and community-wide transmission of the virus occurs mainly in public places where most people are likely to come into contact with the greatest number of possible infection carriers (Chen et al., 2020). Accordingly, in this research, the ten most relevant influential factors for evaluating the vulnerability status of infection risk of COVID-19 in Addis Ababa were selected mainly based on prior knowledge of the property of the pandemic and available literature review (Pourghasemi et al., 2020; Sánchez-Sánchez et al., 2020), which includes, Landuse, Population density, distance from roads, distance from hospitals, distance from bus stations/terminals, distance from the bank, distance to Markets, number of people with COVID-19, distance to health care unite, and distance to government offices. These datasets were collected from various sources and processed using ArcGIS software for MCDA.

The third step was standardizing each factor/ criterion. In this step, data pre-processing, proximity analysis, rasterization, and reclassification are included.

Data Pre-processing: Pre-processing activities made was 4-fold; for number of COVID-19, population number, City Master plan, and GPS (Co-ordinate) data.

The COVID-19 case distribution map is prepared by joining the numerical data of the COVID-19 case distribution with the sub-city shapefile. To pre-process the numerical data, the following systematic steps were followed.

The number of COVID-19 case data was first encoded in an excel sheet with their respective sub-city and saved as CSV (comma delimited) file format. This tabular data is then joined with the attribute table of sub-city shapefile based on a field common to both tables in ArcGIS software, presented in (Appendix-II).

The other pre-processing activities were done for population number data. A similar approach with the above was followed up to joining the numerical data with their respective sub-city in the ArcGIS environment. Then the new population density field was added in the attribute table of the sub-city shape file next. The population density was calculated by applying Equation 3.1 using the field calculator tool in ArcGIS software.

Population Density = Number of People/Land Area (KM^2) …………………………… 3.1

The pre-processing activity for the city master plan was to extract landuse and road features (only main road). These two factors were selected and exported separately from the city master plan by using the Export Data tool in ArcGIS software to get a shapefile of each feature. Various land-use classes in the exported land-use feature are merged into four classes that contribute to the COVID-19 spread using the Merge tool from the editor menu in ArcGIS software. Finally, road and land-use shapefile were prepared for further analysis.

Finally, the GPS (coordinate) data were pre-processed. In this fold, the pre-processing activity involves the conversion of the coordinate data in excel format (CSV comma delimited) to the point feature class (shapefile). This activity was done by using the Export Data tool in ArcGIS software.

Proximity analysis: -In order to generate the vulnerability status of COVID-19 infection risk based on nearness to the transmission source, it is necessary to apply proximity analysis. Proximity analysis is the process of analyzing locations of features by measuring the distance between them and other features in the area. In this study, proximity analysis was done by using Euclidean distance tools for the factors such as Road, Market Place, Bank, Hospital,1st level Clinic, Terminal, and Government office. The ability to generate raster output from vector input without further rasterization process was the cause for using the Euclidean distance tool in this study. Euclidean distance involves determining the straight distance between a map of each cell and a source determined. It is determined from the center of a source cell to the center of each surrounding cell by locating the hypotenuse (Alzamili et al., 2015). The input source data can be a feature class or raster. When the input source data is a feature class, the source locations are converted internally to a raster before performing the analysis. The resolution of the raster can be controlled with the Output cell size parameter or the Cell Size environment. In this study, 30x30 cell size was assigned for all analyses. By default, the resolution will be determined by the shorter width or height of the extent of the input feature, in the input spatial reference, divided by 250. When the input source data is a raster, the set of source cells consists of all cells in the source raster that have valid values. Cells that have No Data values are not included in the source set. The value 0 is considered a legitimate source. A source raster can be easily created using extraction tools. All output raster in Euclidean distance is of floating-point type.

Rasterization; -To make data suit for reclassification and further analysis, vector data have to be rasterized. Simply rasterization is a process of converting vector (feature-based) data into raster (pixel-based) format. This study used a Conversion tool, specifically, polygon to raster tool in ArcGIS environment for the factors of Landuse, Population density, and COVID-19 distribution map. 30x30 cell size was assigned for all raster layers.

Reclassification: -Data depicted on an ongoing scale are the resulting maps generated from the Euclidean analysis and Rasterization. Each range must be assigned a single value before it can be used in the Weighted overlay tool to make comparisons possible. The Reclassify tool allows for such raster to be reclassified. Therefore, in this study, the ranges of values generated in the Euclidean analysis and rasterization were reclassified into 4 groups, using equivalent interval methods in ArcGIS software. A general score ranging from 1 to 4 was allocated to the groups. A score of 1 is the low vulnerable, while a score of 4 is the extremely high vulnerable.

The fourth step was defining weights for each criterion based on its influence on the vulnerability of infection risk of COVID-19. Several methods are available to determine the weight, like Analytical Hierarchy Process (AHP), ranking, and rating. In this study, in assessing the importance of each selected factor, the AHP was used. AHP uses a hierarchical structure; it enables decision-makers to define high-level strategic objectives and specific metrics to better evaluate strategic alignment. It can be applied in any organization with any level of maturity because the inputs are normalized using either numerical data or subjective judgments when metrics are not available, and the process gives itself to sensitivity analysis (Saaty, 1980). In the AHP, all possible combinations of two factors were compared based on expert judgment and consensus on each factor's weight. Then a pairwise comparison matrix was prepared by assessing the factor's importance relative to the importance of the other factor in the pair. As shown in Table 3.3, the importance of each factor relative to the other in a pair would have a value ranging from 1/9 (extremely less important) to 9 (extremely more important). The resulting matrix was used as an input to calculate a set of weights and consistency ratios. The factor weighting process was done by using the IDRISI Selva Software, presented in (Appendix-IV).

Table 3.3: A Nine-point continuous comparison scale

Less important					**More important**			
Extremely	Very strong	Strongly	Moderately	Equally	Moderate	Strongly	Very strong	Extremely
1/9	1/7	1/5	1/3	1	3	5	7	9

Step five was to aggregate the criteria using weighted overlay analysis. Validating the result was the final step. In overlay analysis, different layers were overlaid together with their weights to generate a vulnerability status map using the weighted overlay tool. The weights assigned to the criteria represent the strength of influence of each criterion within the scenario. The values of each pixel from each criterion are multiplied by its corresponding weight (Figure 3.2). This is repeated for each criterion, the resulting values are added and then rounded to the nearest integer before they are assigned to each pixel to obtain a final vulnerability status map. Within the scenario, the lower the cumulative value for each pixel, the lower the vulnerability. Conversely, the higher the cumulative value for each pixel, the higher the vulnerability.

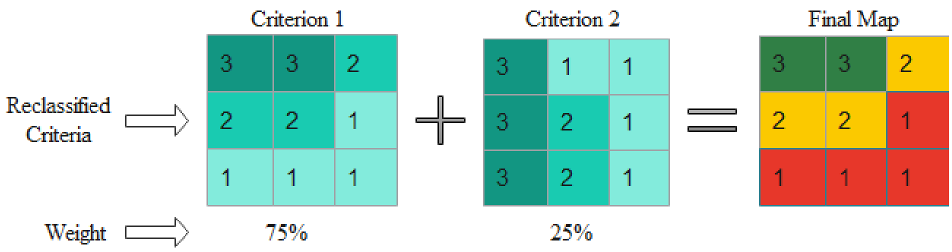

Figure 3.3: A schematic example of the final map generation weight overlay method

CHAPTER IV: RESULT AND DISCUSSION

The results are clearly provided in this section. The predefined methodologies in section 3.4 are followed to generate all the layers and evaluate vulnerability status of infection risk to COVID-19 in the city.

4.1. Factors for COVID-19 Infection Risk Vulnerability Status Evaluation

No	Factors
1	Market place
2	Terminals
3	COVID-19 case
4	Road
5	Government office
6	Hospitals
7	Lower Clinics
8	Banks
9	Population density
10	Landuse

4.2. Vulnerability Status Evaluation with respect to each criterion.

i) Proximity to Marketplace

A Marketplace is a gathering place where people come to buy and sell provisions, livestock, and other goods. It is characterized by concentrating a large number of populations at a certain time. Markets are a critical place of commerce and a source of many essential goods, but they can pose potential risks for the COVID-19 spread (CDC, 2021). In this study, the analysis results show that 0.07 km^2 was found extremely high vulnerable, 0.25 km^2 of the study area is highly vulnerable, 0.4 km^2 was observed as moderately vulnerable area, and the rest 520.20 km^2 of the area is less vulnerable for infection risk of COVID-19 pandemic in terms of proximity to the marketplace. As shown in figure 4.1, an extent of 0.01% of the area was extremely high vulnerable for infection risk of COVID-19. Since the area is the nearest to the marketplace and is highly impacted by the case in the marketplace due to contact between humans, or human to objects. Moreover, 0.05% and 0.08% of the total areas were highly and moderately vulnerable, respectively. The rest 99.87% of area was low vulnerable to infection risk of COVID-19 pandemic due to its farness to transmission center (see Table 4.1)

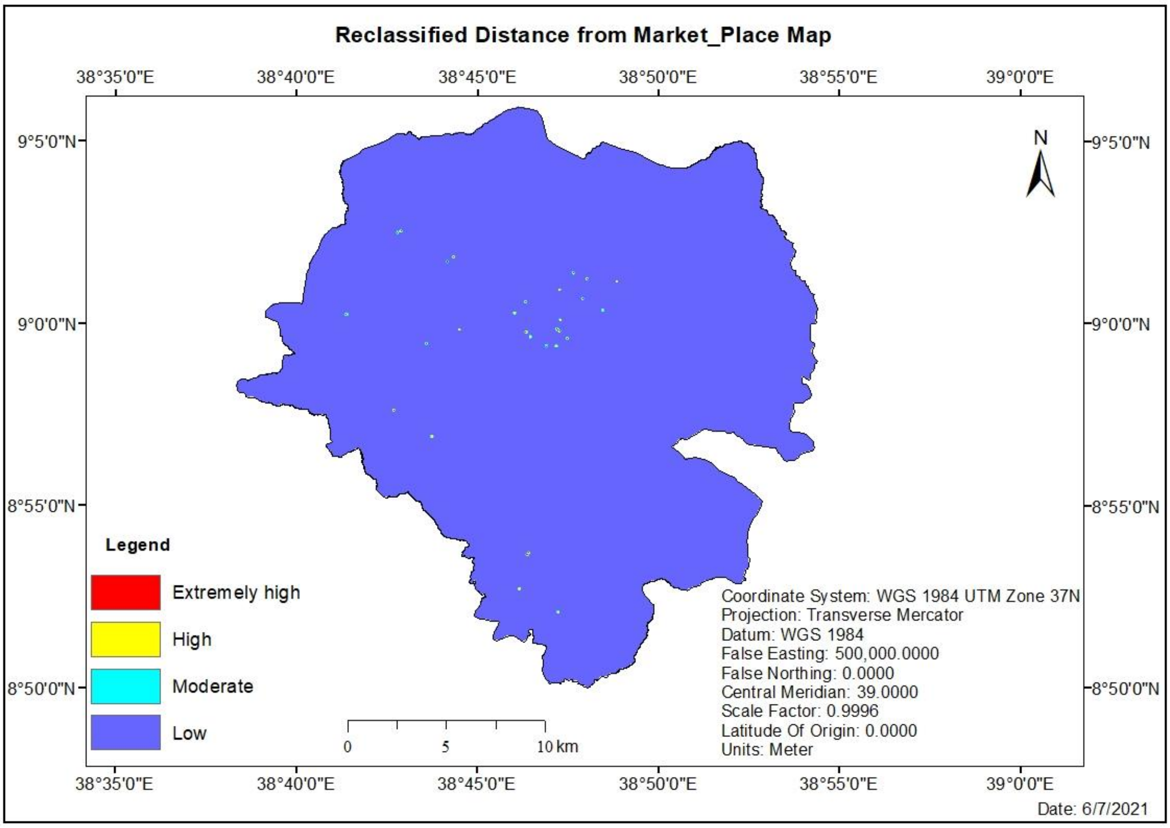

Figure 4.1: Reclassified distance from marketplace map

Table 4.1: Reclassified distance from marketplace and area coverage of vulnerability status

No	Proximity to Market place(m)	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	520.20	99.87	1
2	60-90	Moderate	0.4	0.08	2
3	30-60	High	0.25	0.05	3
4	<30	Extremely high	0.07	0.01	4
Total			520.90	100	

ii) Proximity to Terminals

This involves ground transportation with passenger boarding and disembarking facilities and equipment. The key sites chosen for this criterion were long-distance bus stations, in-town bus stations, and taxi terminals. This factors highly impact the COVID-19 spread. Ren et al.(2020), in their study in China, states that the realistic situations of increasing local transmission featured by familiar clustering in Beijing and Guangzhou could be a reasonable explanation for that marketplace, and the terminals heavily influenced the potential COVID-19 infection risks.

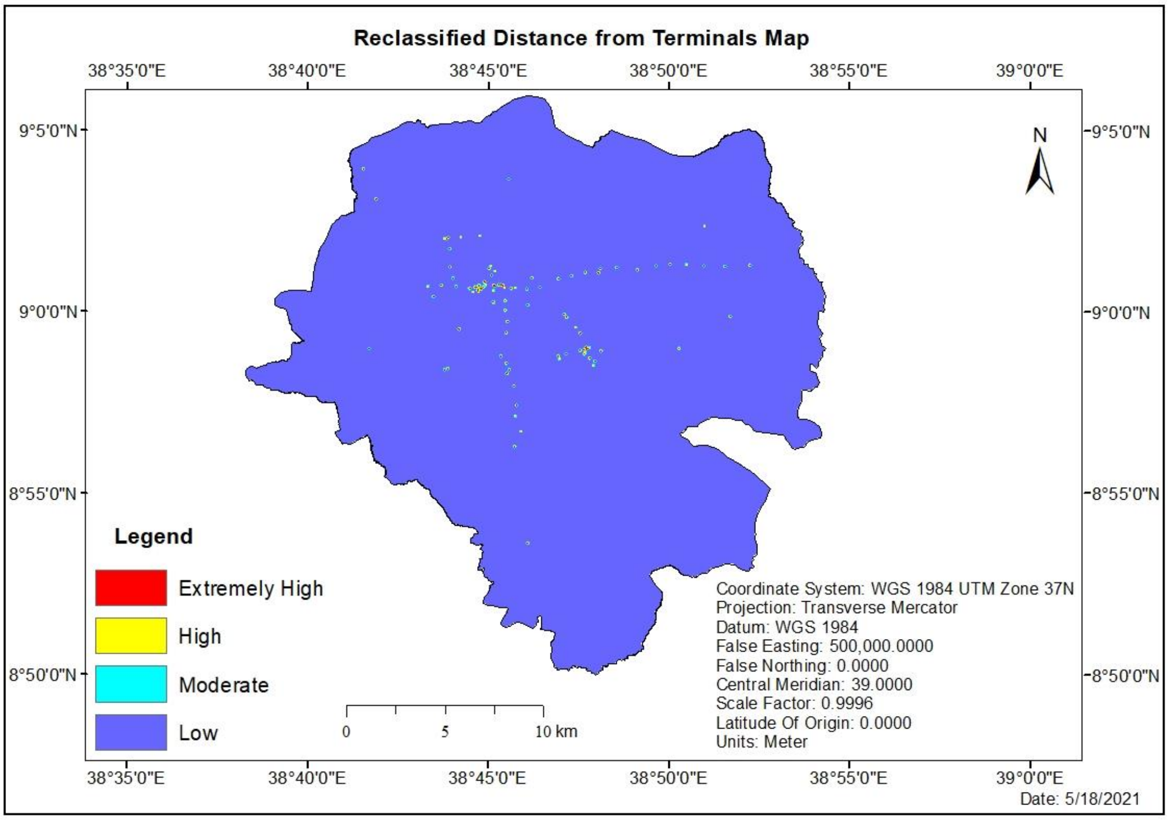

Figure 4.2: Reclassified distance from terminals map

The analysis results show that 0.46km^2 was found extremely high vulnerable, 0.68km^2 is highly vulnerable, 1.17km^2 was observed as moderately vulnerable area, and the rest 518.6km^2 of the area is less vulnerable for infection risk of COVID-19 pandemic. Figure 4.2 shows that 99.56% of the study area is low vulnerable. 0.09% is extremely high vulnerable to infection risk of COVID-19 in terms of proximity to terminals. Also, 0.13% and 0.22% of the study area are high and moderately vulnerable, respectively (see Table 4.2).

Table 4.2: Reclassified distance from terminals and area coverage of vulnerability status

No	Proximity to terminals	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	518.6	99.56	1
2	60-90	Moderate	1.17	0.22	2
3	30-60	High	0.68	0.13	3
4	<30	Extremely high	0.46	0.09	4
Total			**520.90**	**100**	

iii) COVID-19 positive case

These factors include the total number of Covid-19 positive cases in an area. Although the patient was handled in the hospital, poor waste management and a lack of cleaning and sanitation before being tasted can increase the risk of infection among neighbors(Sánchez et al., 2020). The data used in GIS-MCDA are those reported by the Addis Ababa Health Bureau on March 24, 2021.

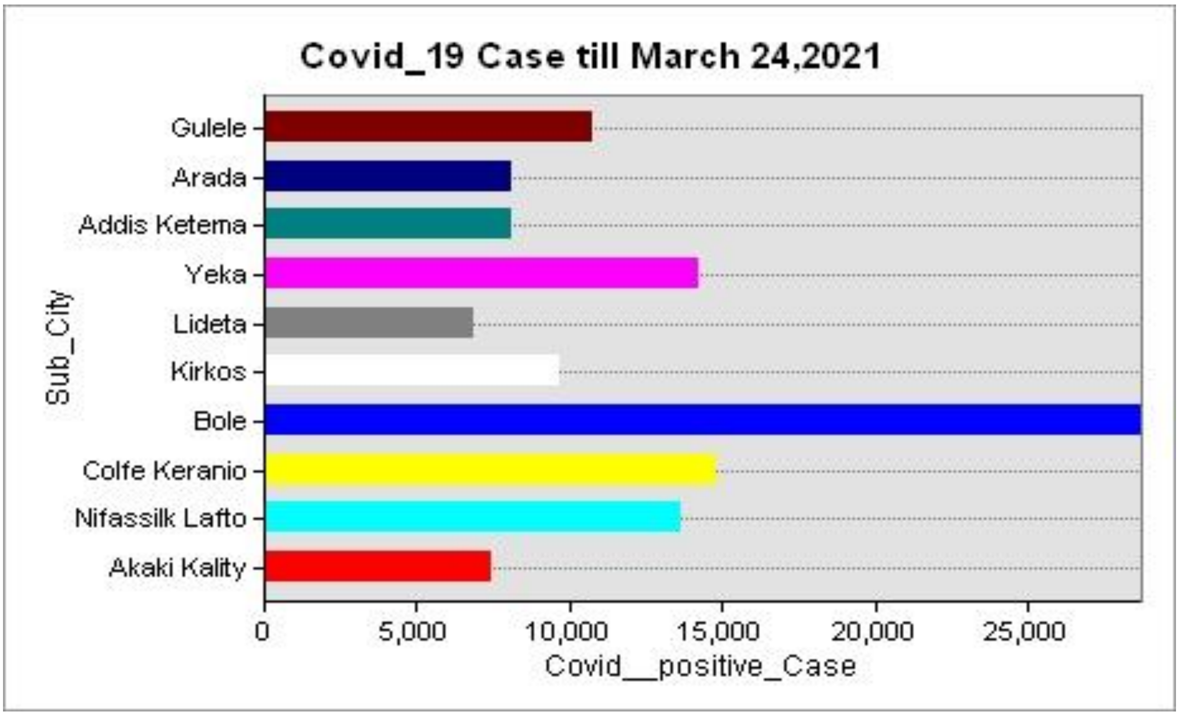

Figure 4.3: COVID-19 confirmed case in Addis Ababa till March 24,2021

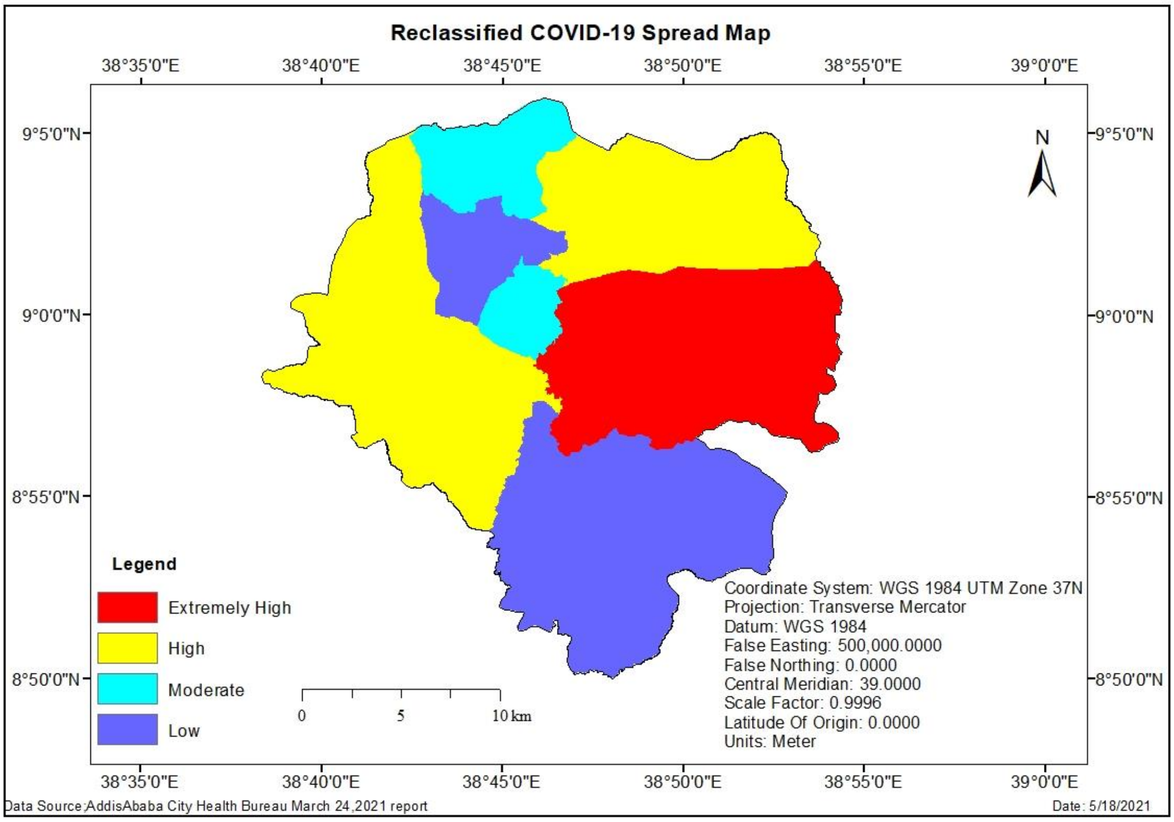

Figure 4.4: Reclassified COVID-19 spread map

The results show that 119.66 km^2 was extremely high vulnerable for infection risk of COVID-19 out of the total study area. The high vulnerable area shared 203.85 km^2. The moderate vulnerable area accounted for 45.84 km^2. The rest area, which is 151.56 km^2, was evaluated as low vulnerable for infection risk of COVID-19. As shown in figure 4.4 29.1% of the study area is less vulnerable. 22.97% of the total study area is extremely high vulnerable for infection risk of COVID-19 from the number of COVID-19 positive case points. Also, 39.13% and 8.8% of the study area are high and moderately vulnerable, respectively (see Table 4.3).

Table 4.3: Reclassified COVID-19 spread and area coverage of vulnerability status

No	**COVID-19 case till March 24, 2021**	**Vulnerability status**	**Area coverage(km^2)**	**% of area coverage**	**Rank**
1	6874-8145	Low	151.56	29.1	1
2	8145-10769	Moderate	45.84	8.8	2
3	10769-14850	High	203.85	39.13	3
4	14850-28735	Extremely high	119.66	22.97	4
Total			**520.90**	**100**	

iv) Proximity to Road

The Euclidean Road distance was reclassified because an area very close to the road is highly vulnerable to infection risk of the COVID-19 pandemic. It is the place where people come in close contact with each other and can be considered significant factors that influence the distribution of COVID-19 (Pourghasemi et al., 2020). Accordingly, an area from 0 to 30m is categorized under extremely high vulnerability. 30 to 60 m and 60 to 90m from the road are high and moderately vulnerable. Moreover, above 90m is classified as less vulnerable to infection risk of COVID-19 pandemic in terms of proximity to the road. Vulnerability status with their area coverage and the scale assigned are summarized in Table 4.4. The results shows that 9.1 km^2 was extremely high vulnerable for infection risk of COVID-19 out of the total study area. The high vulnerable area shared 13.35 km^2. The moderate vulnerable area accounted for 17.14km^2. The rest area, which is 481.32 km^2, was evaluated as low vulnerable for infection risk of COVID-19. Means that 92.4% of the study area is low vulnerable, 1.75% of the total study area is extremely high vulnerable to infection risk of COVID-19 in terms of proximity to road and 2.56% and 3.29% of the study area are high and moderately vulnerable respectively (see Table 4.4).

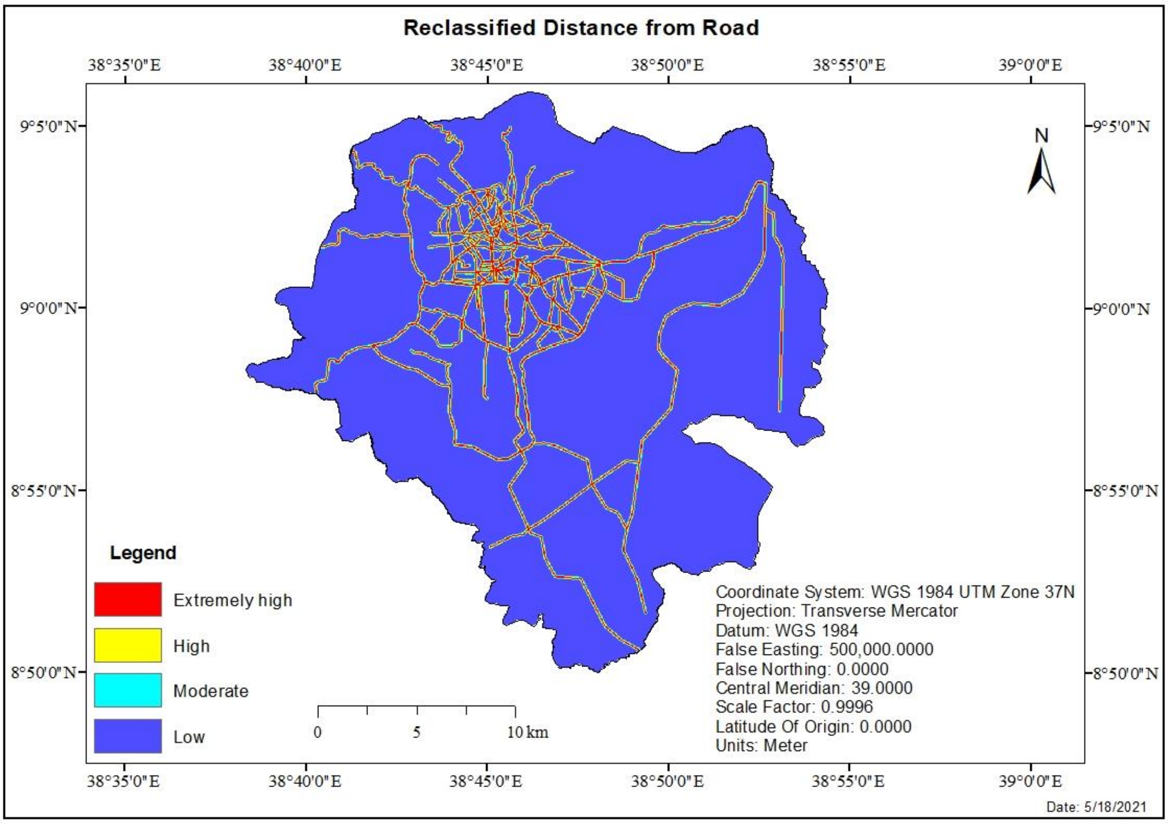

Figure 4.5: Reclassified distance from road map

Table 4.4: Reclassified distance from road and area coverage of vulnerability status

No	Proximity to the road(m)	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	481.32	92.4	1
2	60-90	Moderate	17.14	3.29	2
3	30-60	High	13.35	2.56	3
4	<30	Extremely high	9.1	1.75	4
Total			**520.90**	**100**	

v) Proximity to Hospitals

A hospital is a health care institution providing patient treatment with specialized medical and nursing staff and medical equipment. This criterion includes the hospitals and establishments where services related to internal medicine, pediatrics, gynecology, obstetrics, general surgery, and psychiatry are provided (Sánchez-Sánchez et al., 2020). It can be considered as a COVID-19 vulnerability factor, because it is most exposed to contagion due to the type of service offered during the 24 h. In addition to the patient seeking late help, he comes when his symptoms are shortness of breath and oxygen, giving a possible case of Covid-19. This condition makes it riskier and increases the probability of being transmitted horizontally, to the point of causing saturation in-hospital services, causing them to collapse due to the number of people seeking care without need, in addition to the relatives of hospitalized patients who are heavily exposed to contagion when meeting in the emergency and hospitalization areas without respecting prevention and hygiene protocols. The results shows that 2.56 km^2 was extremely high vulnerable for infection risk of COVID-19 out of the total study area. The high vulnerable area shared 6.79 km^2. The moderate vulnerable area covers 2.91 km^2 of an area. The rest area, which is 508.68 km^2, was evaluated as low vulnerable for infection risk of COVID-19. This indicated that 97.65% of the study area is less vulnerable. 0.49% of the total study area is extremely high vulnerable to infection risk of COVID-19 in terms of proximity to hospitals. Also, 1.3% and 0.56% of the study area are high and moderately vulnerable, respectively (see Table 4.5).

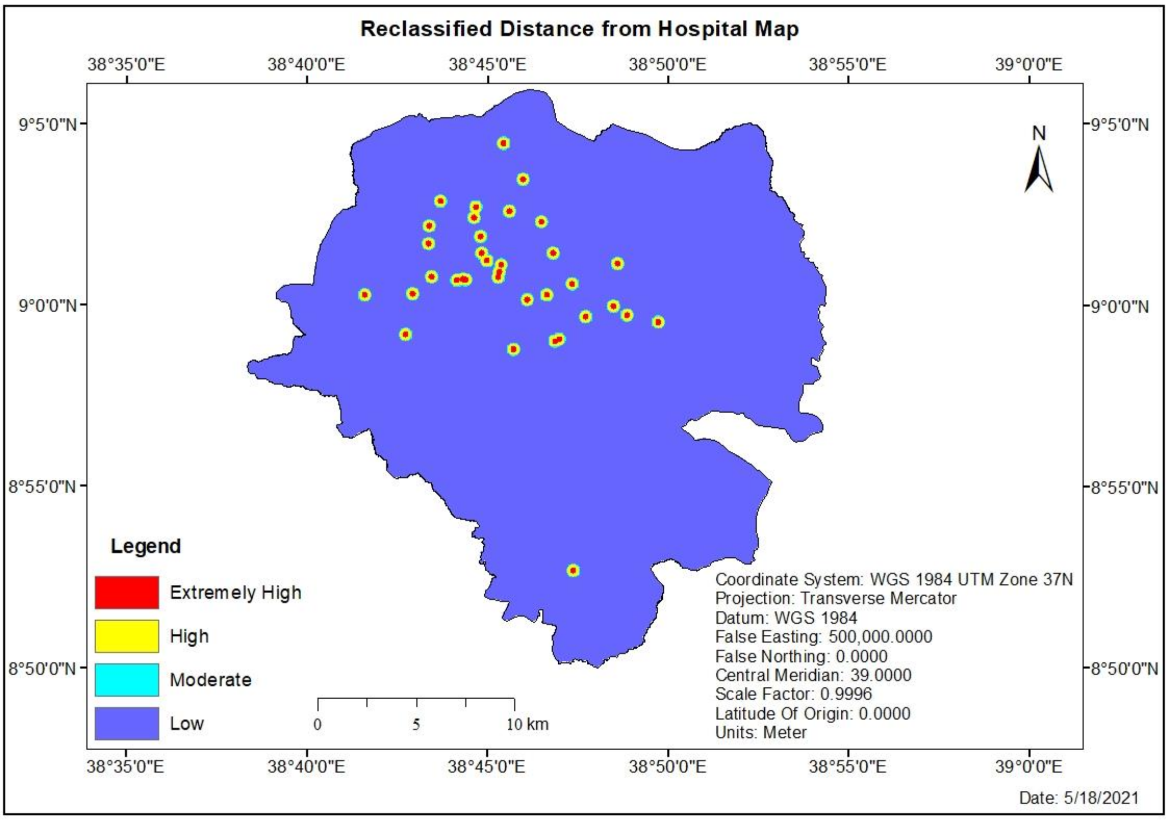

Figure 4.6: Reclassified distance from hospitals map

Table 4.5: Reclassified distance from hospitals and area coverage of vulnerability status

No	Proximity to hospitals	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	508.68	97.65	1
2	60-90	Moderate	2.91	0.56	2
3	30-60	High	6.79	1.3	3
4	<30	Extremely high	2.56	0.49	4
Total			**520.90**	**100**	

vi) Proximity to Lower Clinics

The lower Clinics include the spaces that provide outpatient care for the most frequent morbidity and are dedicated to health care, prevention and promotion and are recognized by the population as local health benchmarks. In this study, the analysis results show that 0.48 km^2 was found extremely high vulnerable, 1.46 km^2 of the study area is highly vulnerable, 2.14 km^2 was observed as a moderately vulnerable area and the rest 516.86 km^2

of the area which is less vulnerable for infection risk of COVID-19 pandemic in terms of proximity to lower clinics.

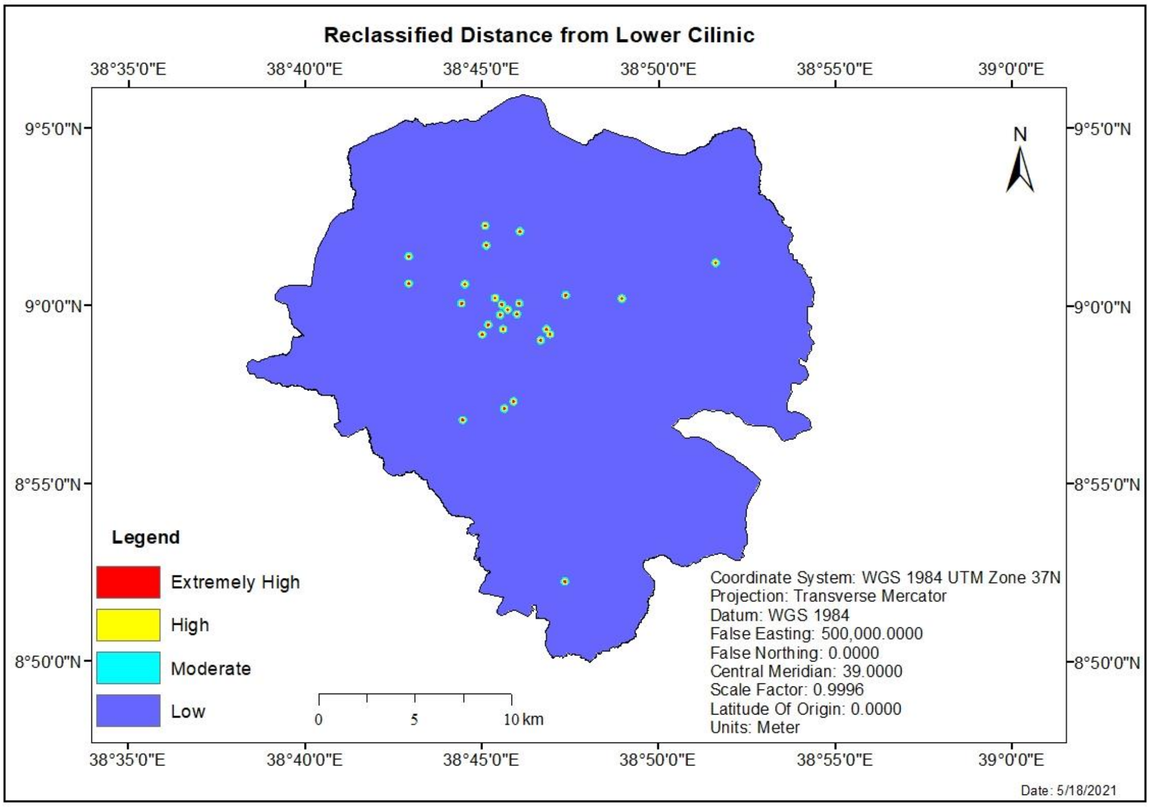

Figure 4.7: Reclassified distance from lower clinics map

The result in figure 4.7 shows that 99.22 % of the study area is low vulnerable. 0.09% of the total study area is extremely high vulnerable to infection risk of COVID-19 in terms of proximity to lower clinics. Also, 0.28% and 0.41% of the study area are high and moderately vulnerable respectively (see Table 4.6).

Table 4.6: Reclassified distance from lower clinics and area coverage of vulnerability status

No	**Proximity to lower clinics**	**Vulnerability status**	**Area coverage(km^2)**	**% of area coverage**	**Rank**
1	>90	Low	516.86	99.22	1
2	60-90	Moderate	2.14	0.41	2
3	30-60	High	1.46	0.28	3
4	<30	Extremely high	0.48	0.09	4
Total			**520.90**	**100**	

vii) Proximity to Banks

Financial institutions dedicated to money management such as banks and ATMs are included in this criterion. People visit them daily to conduct a variety of transactions and have a high influence on the COVID-19 spread. In this study, the analysis results show that 0.43km^2 was found extremely high vulnerable, 0.67 km^2 of the study area is highly vulnerable, 1.19 km^2 was observed as a Moderately vulnerable area, and the rest 518.62 km^2 of the area is less vulnerable for infection risk of COVID-19 pandemic. Figure 4.8 shows that 99.56% of the study area is less vulnerable. On the other hand, 0.08% of the total study area is extremely high vulnerable to infection risk of COVID-19 from the number of COVID-19 positive case points. Also, 0.13% and 0.23% of the study area are high and moderately vulnerable, respectively, in proximity to the bank (see Table 4.7).

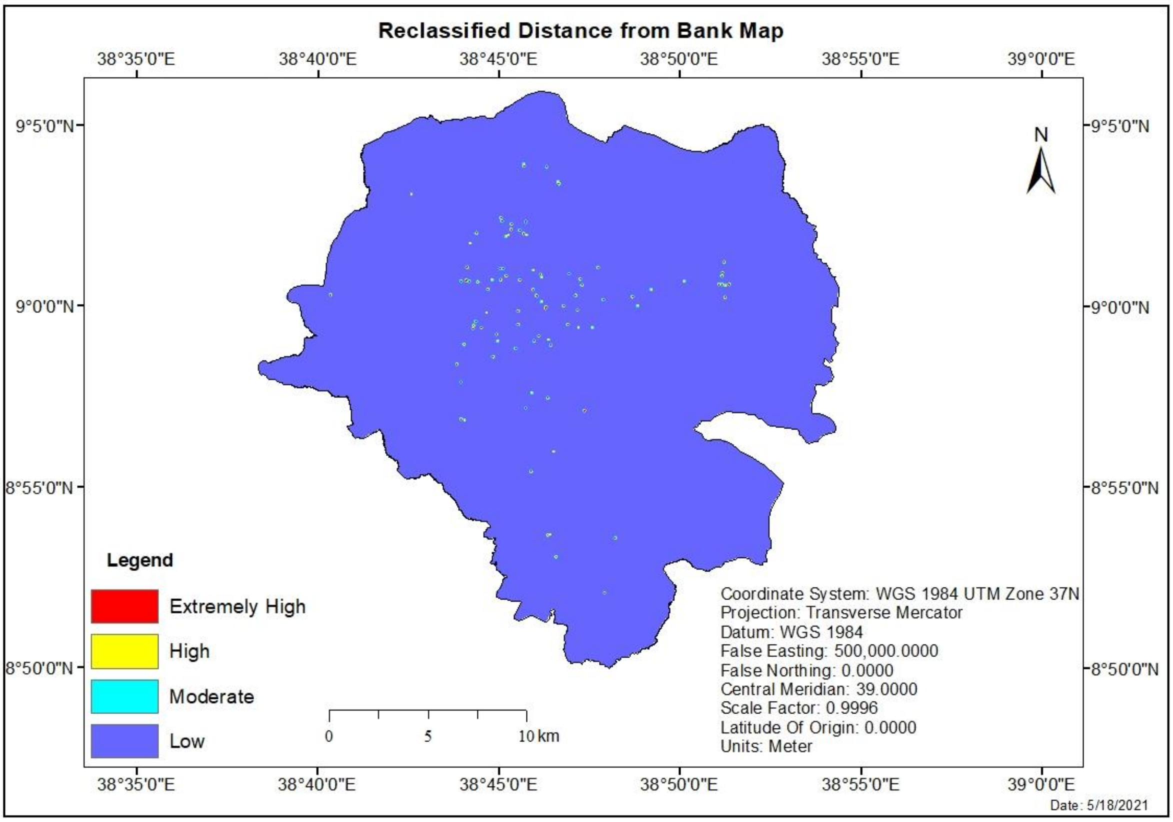

Figure 4.8: Reclassified distance from banks map

Table 4.7: Reclassified distance from banks and area coverage of vulnerability status

No	Proximity to Bank	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	518.62	99.56	1
2	60-90	Moderate	1.19	0.23	2
3	30-60	High	0.67	0.13	3
4	<30	Extremely high	0.43	0.08	4
Total			**520.90**	**100**	

viii) Proximity to Government office

Government offices include all institutions dedicated to public administration and management at the federal, city, sub-city, and wereda levels. It is characterized by a collection of a high number of people who need their service. This makes it more vulnerable to the infection risk of COVID-19. In this study, the analysis results show that 0.29 km^2 was found extremely high vulnerable, 0.9 km^2 of the study area is highly vulnerable, 1.37 km^2 was observed as a moderately vulnerable area, and the rest 518.35 km^2 of the area is less vulnerable to infection risk of COVID-19 pandemic.

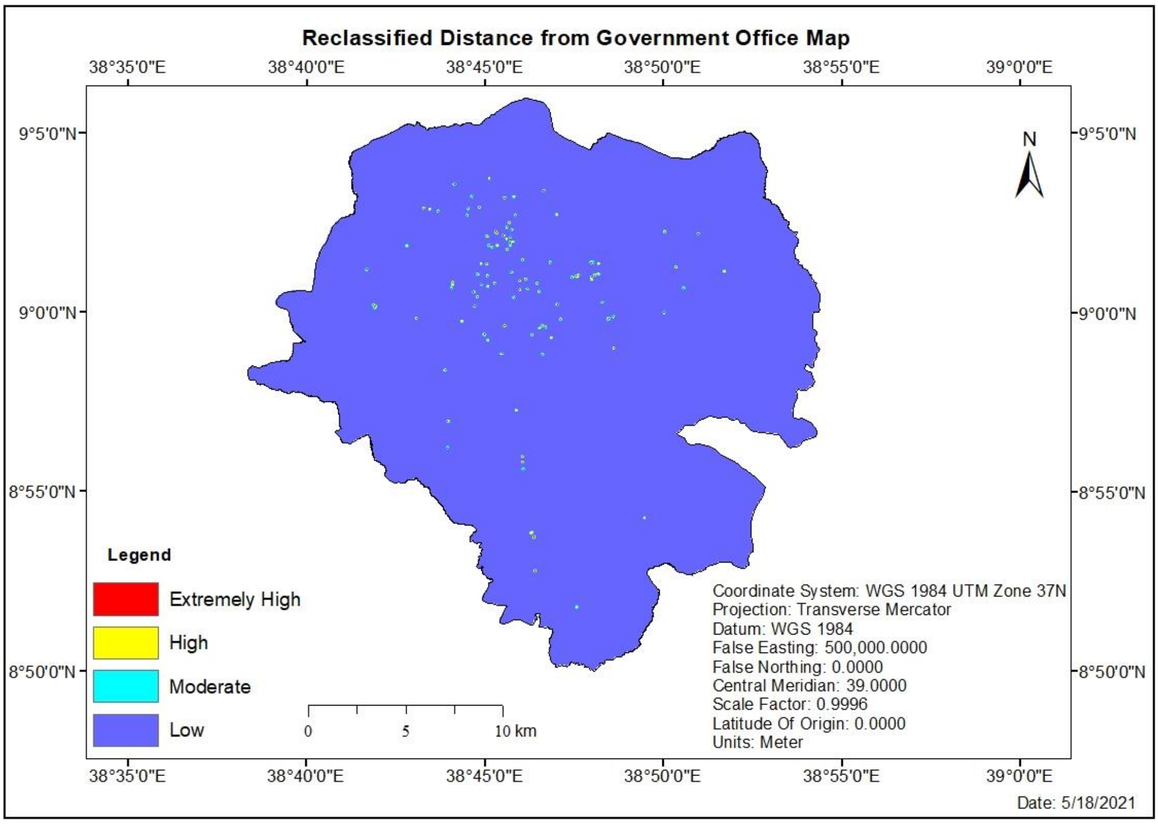

Figure 4.9: Reclassified distance from government offices map

Figure 4.9 shows that 99.51% of the study area is less vulnerable. On the other hand, 0.06% of the total study area is extremely high vulnerable to infection risk of COVID-19 from the number of COVID-19 positive case points. Also, 0.17% and 0.26% of the study area are high and moderately vulnerable, respectively, in proximity to a government office (see Table 4.8).

Table 4.8: Reclassified distance from government office and area coverage of vulnerability status

No	Proximity to Government Office	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	>90	Low	518.35	99.51	1
2	60-90	Moderate	1.37	0.26	2
3	30-60	High	0.9	0.17	3
4	<30	Extremely high	0.29	0.06	4
Total			**520.90**	**100**	

ix) Population density

Population density is the number of individuals per unit geographic area. It allows for a broad comparison of settlement intensity across geographic areas. They are typically expressed as the number of people per square kilometer of land area (Cohen, 2015). High population density causes favorable condition for the transmission of COVID-19(Unhale et al., 2020). In this study, the analysis results show that 8.63 km^2 was found extremely high vulnerable,142.93 km^2 of the study area is highly vulnerable, 14.65 km^2 was observed as a moderately vulnerable area and the rest 354.69 km^2 of the area which is less vulnerable for infection risk of COVID-19 pandemic. Figure 4.10 shows that an extent of 1.66% of the area was extremely high vulnerable for infection risk of COVID-19 due to the dense population, hence, urban sectors with high population density are more vulnerable to the spread of contagious diseases. This is due to space limitations within and between households, high mobility, and limited water, sanitation, and hygiene infrastructure. 27.44% and 2.81% of the total areas were highly and moderately vulnerable, respectively. Moreover, 68.09 % of the study area was less vulnerable due to its dispersed population, and hence it’s less vulnerable to COVID-19 transmission (see Table 4.9).

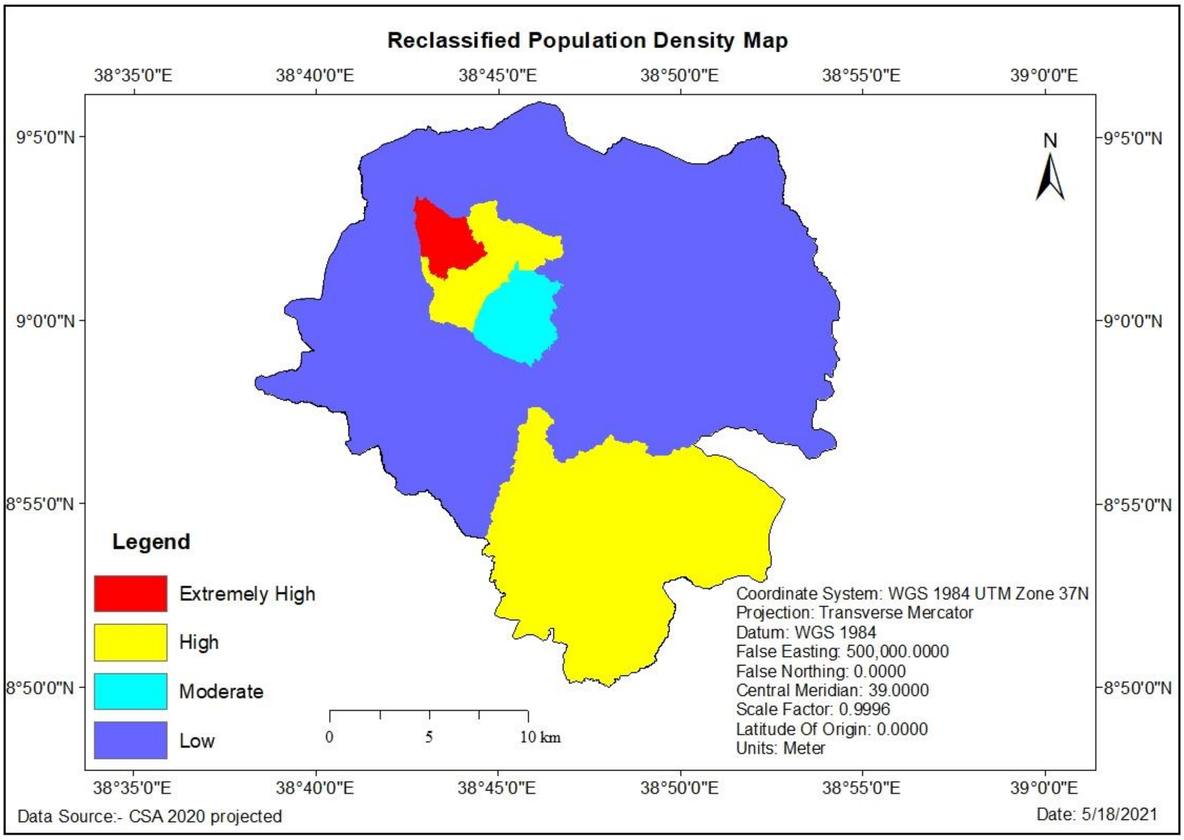

Figure 4.10: Reclassified population density map

Table 4.9: Reclassified population density and area coverage of vulnerability status

No	Population density per km2	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	3,479-5,615	Low	354.69	68.09	1
2	5,615-11,456	Moderate	14.65	2.81	2
3	11,456-20,287	High	142.93	27.44	3
4	20,287-39,801	Extremely high	8.63	1.66	4
Total			**520.90**	**100**	

x) Landuse

Landuse refers to the purpose the land serves, for example, recreation, commercial, residential…etc.; it does not describe the surface cover on the ground (Coffey, 2013). In this study, all landuse classes in the city were categorized into four. Commerce, mixed residence, service (Administrative service, municipal service, social service, infrastructure service, transport, and street network), and Miscellaneous (Environmental protection, manufacturing and storage, special projects, sports fields, urban agriculture, and historical conservation site). The result has shown that an extent of 1.44% of the area was extremely high vulnerable for infection risk of COVID-19. The area with extremely high vulnerability status to infection risk of COVID-19 is a commercial area since urban sectors with commercial landuse classes are more exposed to the spread of contagious diseases. This is due to space limitations within an area, high mobility, and a high degree of people and people's access to object contact. 7.68% and 42.38% of the total areas were highly and moderately vulnerable, respectively, and had mixed residence and service, landuse classes. Finally, 48.50% of the study area with miscellaneous landuse classes was less vulnerable to the infection risk of COVID-19.

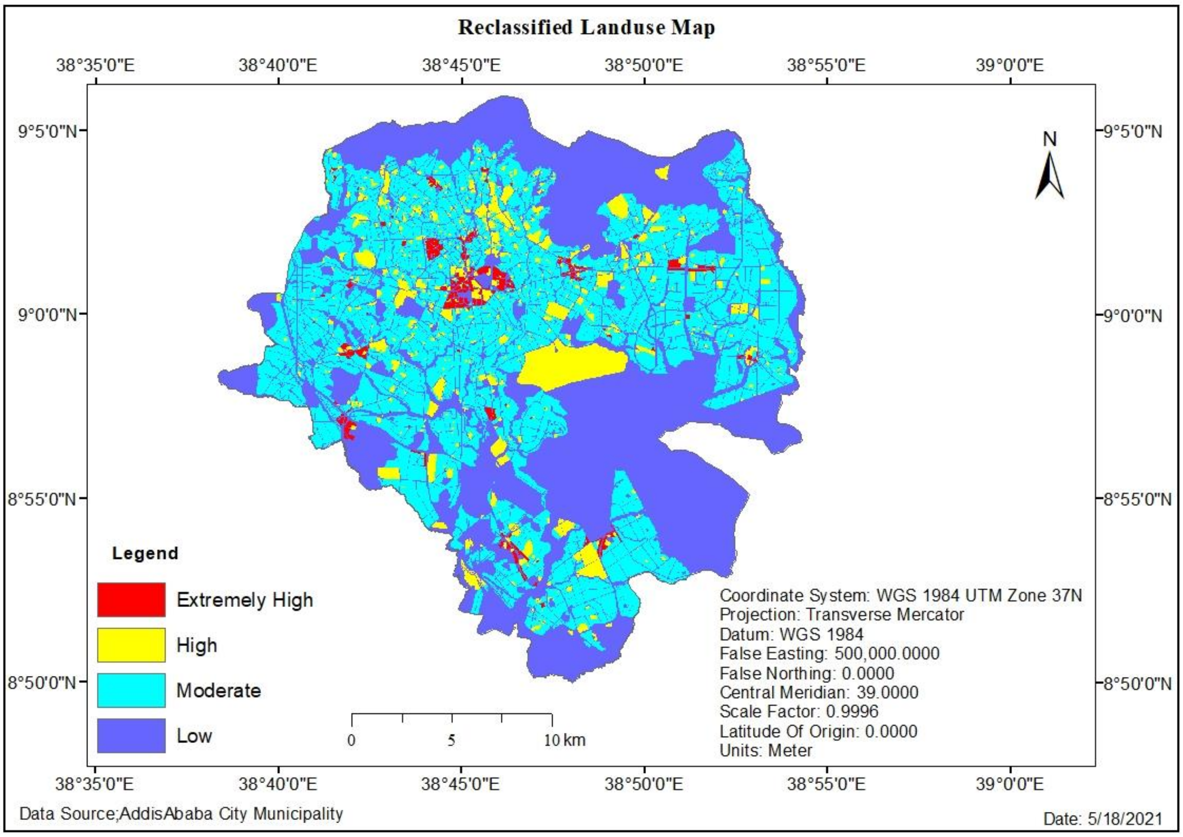

Figure 4.11: Reclassified Landuse map

Table 4.10: Reclassified Landuse and area coverage of vulnerability status

No	Landuse type	Vulnerability status	Area coverage(km^2)	% of area coverage	Rank
1	Miscellaneous	Low	252.69	48.50	1
2	Service	Moderate	220.78	42.38	2
3	Mixed residence	High	40.03	7.68	3
4	Commerce	Extremely high	7.48	1.44	4
Total			**520.90**	**100**	

The analysis results show that 7.48 km^2 was found extremely high vulnerable,40.03 km^2 of the study area is highly vulnerable, 220.78 km^2 was observed as a moderately vulnerable area and the rest 252.69 km^2 of the area which is low vulnerable for infection risk of COVID-19 pandemic in terms of landuse type.

4.3. Criteria Weight Assignment

In particular, ten weights were defined and calibrated using the multicriteria approach through the AHP technique (Table 4.11). The resulting influence was expressed as a percentage. Public markets (31%) were the most important criterion due to the strong concentration of people who visit them to do their shopping, in addition to the small spaces that exist in them. The second influential factor was the terminals (19%). The key sites chosen for these criteria were long-distance bus stations, in-town bus stations, and taxi terminals it is characterized by high mobility and contacts, which increases the risk of COVID-19 infection. The third strongest criterion was people infected with Covid- 19 (18%) due to the ability to transmit the virus to other people such as family and friends who do not respect prevention and hygiene measures. Finally, the criteria Roads (9%), Government offices (6%), Hospitals (5%), Lower Clinics (4%), Banks (3%), Population Density (3%), and Landuse (2%) were the criteria with lower weight of importance without discrediting its value in the general analysis. The AHP weight derivation interface to derive the weights, with its consistency ratio, is shown in vulnerability status evaluation (Figure.4.11). The resulting weights were used as input for the weighted linear combination of overlay analysis.

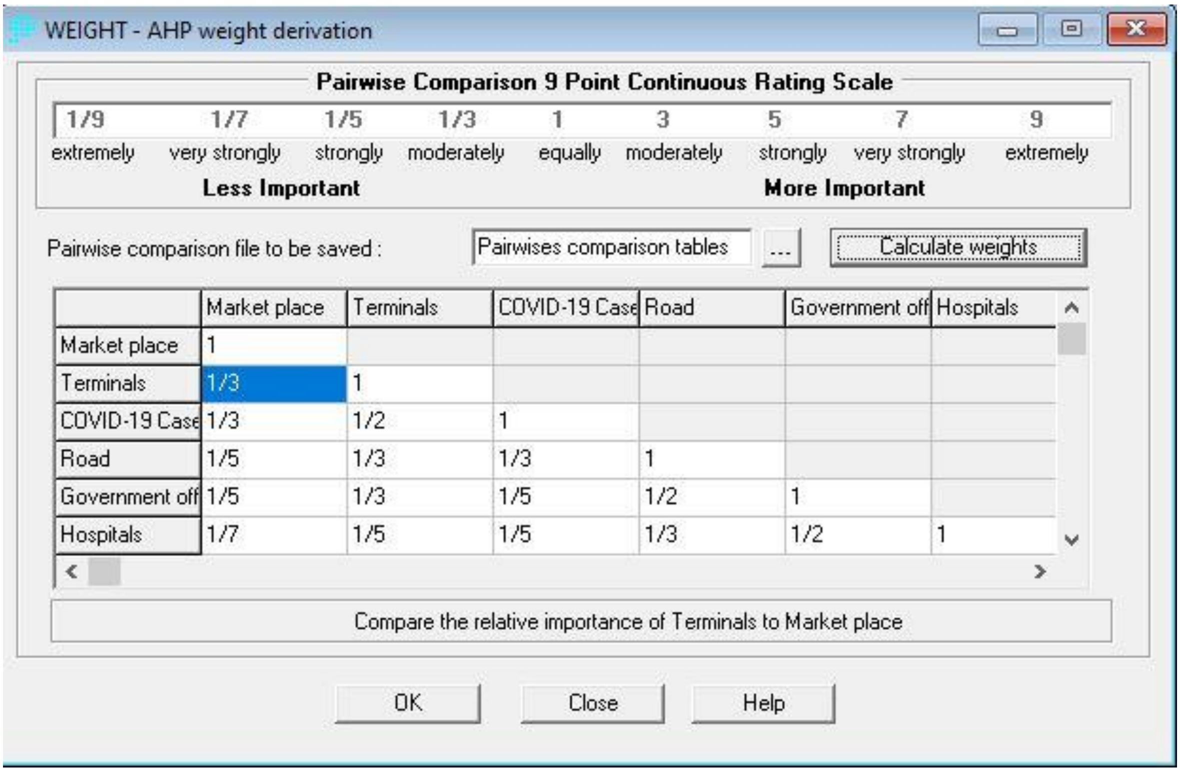

Figure 4.12: AHP weight derivation method of Point Continuous Scale

According to Al-Hanbali A (2011), if the consistency ratio is less than or equal to 0.1, it signifies an acceptable reciprocal matrix. The consistency ratio of this study indicated that 0.06. It is acceptable.

CR = Consistency Index (CI)/Random Consistency Index (RI) (Table 12) ……………. (4.1)

CI = (λmax – n)/n – 1 ……………………………………………………….………… (4.22)

Where λ max is the Principal Eigen Value; n is the number of factors

λmax = Σ of the products between each element of the priority vector and column totals.

Table 4.12: Random Consistency Index (RI)(Saaty, 1980).

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Accordingly, the following eigenvectors of weights for all factors considered for vulnerability status evaluation of COVID-19 infection risk are generated (see Table 4.11).

Table 4.11: Factors and their eigenvectors weights

Factors	Mp	T	C	R	Go	H	LC	B	Pd	LU	Weight	Percent of weight
Market place(Mp)	1										0.3100	31
Terminals(T)	1/3	1									0.1938	19
COVID-19 case(C)	1/3	1/2	1								0.1748	18
Road(R)	1/5	1/3	1/3	1							0.0872	9
Government office(Go)	1/5	1/3	1/5	1/2	1						0.0643	6
Hospiatals(H)	1/7	1/5	1/5	1/3	1/2	1					0.0509	5
Lower Clinics(LC)	1/7	1/5	1/5	1/3	1/3	1/2	1				0.0436	4
Banks(B)	1/7	1/7	1/5	1/3	1/2	1/3	1/3	1			0.0311	3
Population density(Pd)	1/7	1/7	1/7	1/3	1/3	1/2	1/2	1/2	1		0.0267	3
Landuse(LU)	1/7	1/7	1/7	1/5	1/3	1/5	1/5	1/3	1/3	1	0.0177	2
Total											**1**	**100**

Consistency ratio = 0.06<0.1 = Consistency is acceptable.

Table 4.13: The Weight of Factors from the pair-wise comparison eigenvectors.

No	Factors	Weight	Percent of weight
1	Market place(Mp)	0.3100	31
2	Terminals(T)	0.1938	19
3	COVID-19 case(C)	0.1748	18
4	Road(R)	0.0872	9
5	Government office(Go)	0.0643	6
6	Hospiatals(H)	0.0509	5
7	Lower Clinics(LC)	0.0436	4
8	Banks(B)	0.0311	3
9	Population density(Pd)	0.0267	3
10	Landuse(LU)	0.0177	2
Total		**1**	**100**

4.4. Overlaying and COVID-19 infection risk Vulnerability status evaluation

Using the weight of Factors from the pair-wise comparison eigenvectors and the reclassified factors layer as an input, four areas of Covid-19 infection risk vulnerability were obtained for weighted overlay analysis in ArcGIS, as shown in figure 4.16. The result showed that out of the total study area, 32.62% (169.91 km^2) fall under Low vulnerable (1), and the area which covers 40.9% (213.04 km^2) is under moderate vulnerable class (2) for infection risk of COVID-19. The highly vulnerable (3) covers an area of 25.31% (132.87 km^2), and the remaining 1.17% (6.12 km^2) is under an extremely high vulnerable class (4). The result allowed defining various areas with extremely high vulnerability, most of the areas are located in the central part of the city, such as Bole and Megenagna where most of the establishments for public use are located. However, due to the conditions of the criteria, it is possible to observe large areas scattered throughout the city, covering different urban sectors. The areas are characterized by high vehicle-pedestrian traffic. The areas with high vulnerability are delimited mostly in the Bole sub-city. Hence, the area is characterized by a high number of COVID-19 confirmed cases in the city according to city health burau's report. The area with high vulnerability is also delimited in the main road around most parts of the city. The area of moderate vulnerability is located in western, northeastern, and partially central parts of the city. Finally, low vulnerability zones found in the city's northern and southern regions showed a steadier pattern.

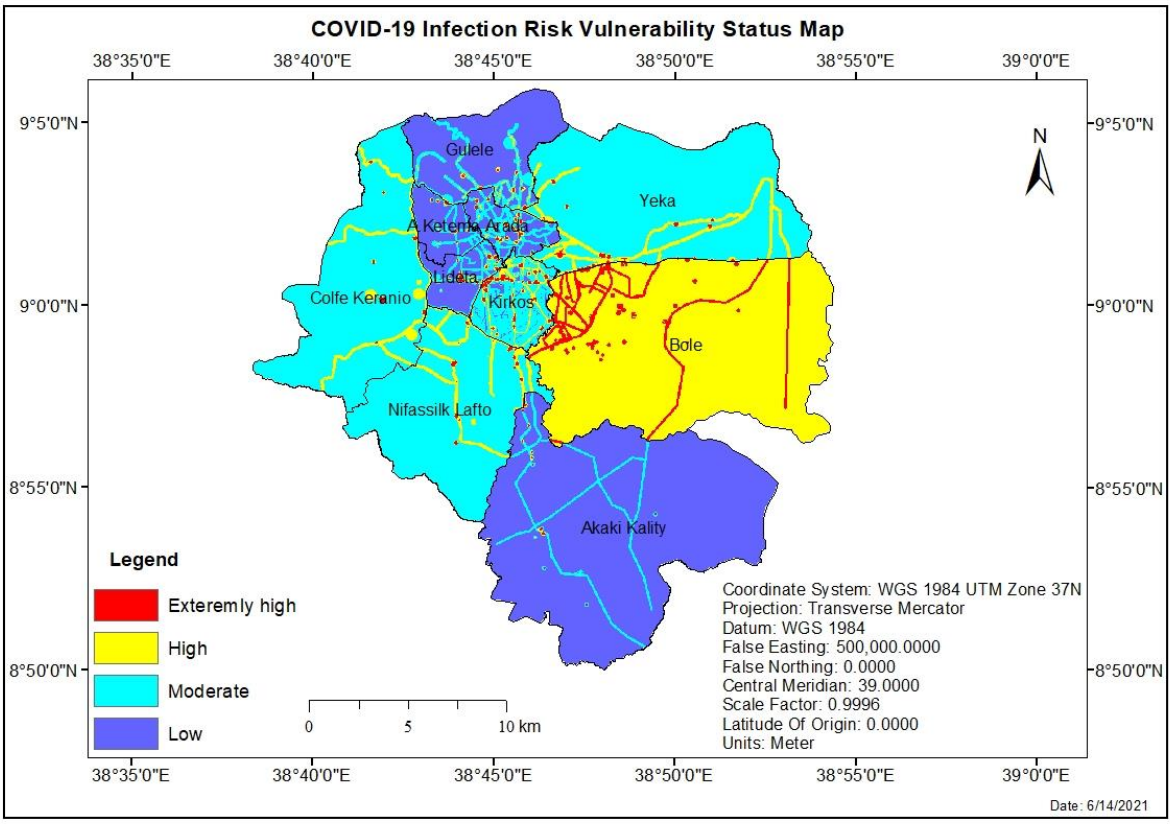

Figure 4.13: COVID-19 Infection risk vulnerability status map in Addis Ababa

Table 4.14: The vulnerability status and the percent of total area coverage of the study area.

Vulnerability status	**Area coverage(km^2)**	**% of area coverage**	**Rank**
Low	169.91	32.62	1
Moderate	213.04	40.9	2
High	132.85	25.31	3
Extremely high	6.12	1.17	4
Total	**520.90**	**100**	

In this study, GIS-MCDA based COVID-19 infection risk vulnerability status evaluation method is applied. This is the first time this approach is proposed for use in COVID-19 vulnerability evaluation in Ethiopia. This can be considered to be a significant step forward for the health sector in the application of geospatial technologies to support pandemic control strategies and decision-making. This research can make a substantial contribution to the health sector for the smooth and effective implementation of adopted epidemic prevention and control strategies. Since the determination of infection risk vulnerability requires exploiting Epidemiology, and GIS, this multidisciplinary knowledge required the cooperation of various experts. Each of infection risk vulnerability evaluation input factors selected for the study have their own level of significance. The resulting findings showed that the highest and lowest significant factors in this study area were marketplace (31%) and Landuse (2%) respectively. The result of this study is consistent with the argument that the place with higher mobility and interaction has a high tendency of being a COVID-19 infection risk vulnerable area. The study indicated that a higher mobility and crowdedness results in a higher probability of COVID-19 spread, and hence a higher COVID-19 infection risk vulnerability status. Vulnerability in a broad context is a complex process that requires an understanding of different input factors. However, the previous studies were based on only a few infection risk vulnerability factors as this research incorporates various infection risk vulnerability input factors. Despite the success demonstrated, due to the inadequacy of data in terms of quality and quantity, the full potential of the GIS-MCDA has not been proven. Thus, further improvements are expected to result in better understanding of the infection risk vulnerability status, by considering much more comprehensive criteria and accurate data. According to different researches conducted so far, validation is an important method of verification either by practical observation or any related researches conducted before. For the current research validation was based on consistency measurement. As vulnerability is a multifaceted process, these selected factors are consistent and common in COVID-19 infection risk vulnerability status evaluation studies. There is no hazard map prepared for all triggering factors included in this study and no prior researches in the area, the measure of consistency is employed to validate the current study.

CHAPTER V: CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The study evaluates the vulnerability status of infection risk to COVID-19 by integrating Geographic Information Systems and Multi-Criteria Decision Analysis for Addis Ababa City. This research has shown that GIS integrated with MCDA is important to create operational maps which could help the health officials and all concerned to identify vulnerable and priority areas for disease control.

The result indicates that the study area experienced extreme vulnerability to low vulnerability status of infection risk of COVID-19. According to the study results, hotspot areas or areas with extremely high vulnerability (2.25%), located in the central part of the city such as Megenagna, Bole international airport areas and in an area collected by various services. The areas with high vulnerability (25.46%) were delimited mostly in the Bole sub-city. Hence, the areas are characterized by a high number of COVID-19 confirmed cases in the city. Also, the areas with high vulnerability delimited in the main road around most parts of the city. On the other hand, the areas of moderate vulnerability (41.14%) were in western, northeastern, and partially central parts of the city and without a defined pattern and the areas of low vulnerability (31.15%) presented a more stable pattern in northern and southern parts of the city. Despite having the highest percentage of surface, the fact of not being close to or immersed in points of high confluence means that these areas are not risky and can be passable by applying prevention measures and security established by local governments. Hence, the maps were constructed to allow targeting intervention within the city according to the vulnerability gradient. Thus, pandemic control mechanisms like disinfection could be addressed regularly to these priority zones.

5.2. Recommendation

The findings of this particular study have shown that GIS-MCDA is useful tools for studies of infection risk vulnerability status evaluation. The following are also recommended as potential research recommendations, based on the results of the study:

i. One of the results noticed in this study was an area with cluster of services and high mobility are at status of extremely high vulnerability to infection risk of COVID-19. Therefore, proper strategies have to be implemented to halt the spread of the disease with special attention in those areas.

ii. The City should develop the capacity to use GIS and MCDA to identify the vulnerability status of infection risk of COVID-19 and related activity in the city.

iii. It will be efficient if the city will incorporate the infection risk vulnerability status maps, which is the results of this study, in the current ongoing pandemic control activates to target the priority areas identified by the study;

iv. The establishment of health centers and other pandemic control facilities should be made at high and extremely high-vulnerable areas at a reasonable distance away from the existing facilities so that people at a distance can easily access the service.

v. Proper databases about detailed patient data, the spatial spread of epidemics, and other related aspects of the pandemic should be made using GIS.

SPECIAL ACKNOWLEDGMENT

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ASTU/SM-R/192/21

Adama, Ethiopia

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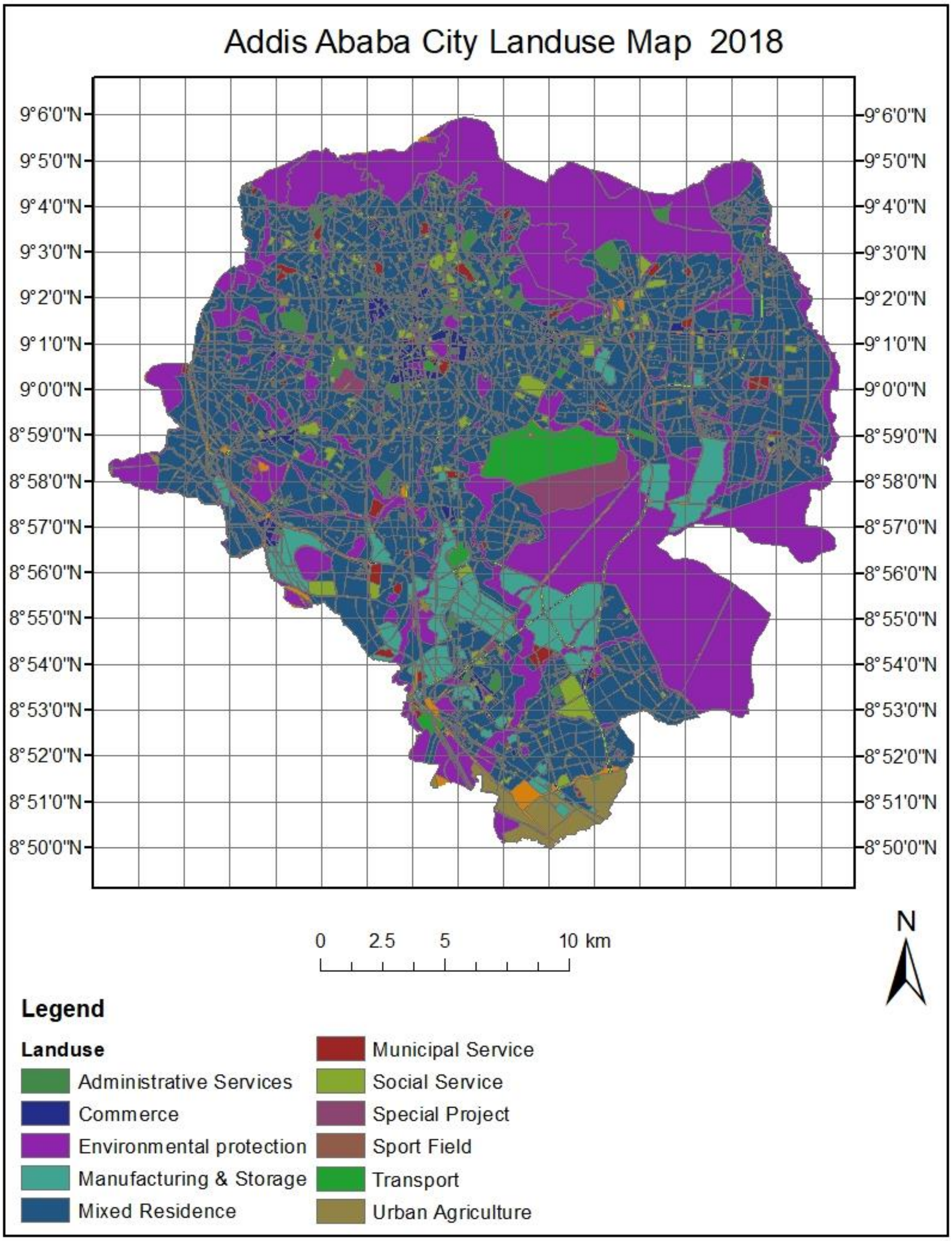
APPENDICES

Appendix I: Landuse map 2018 of the study area



Appendix II: Subcity and COVID-19 cases joined table

Table

Covid_19_spread

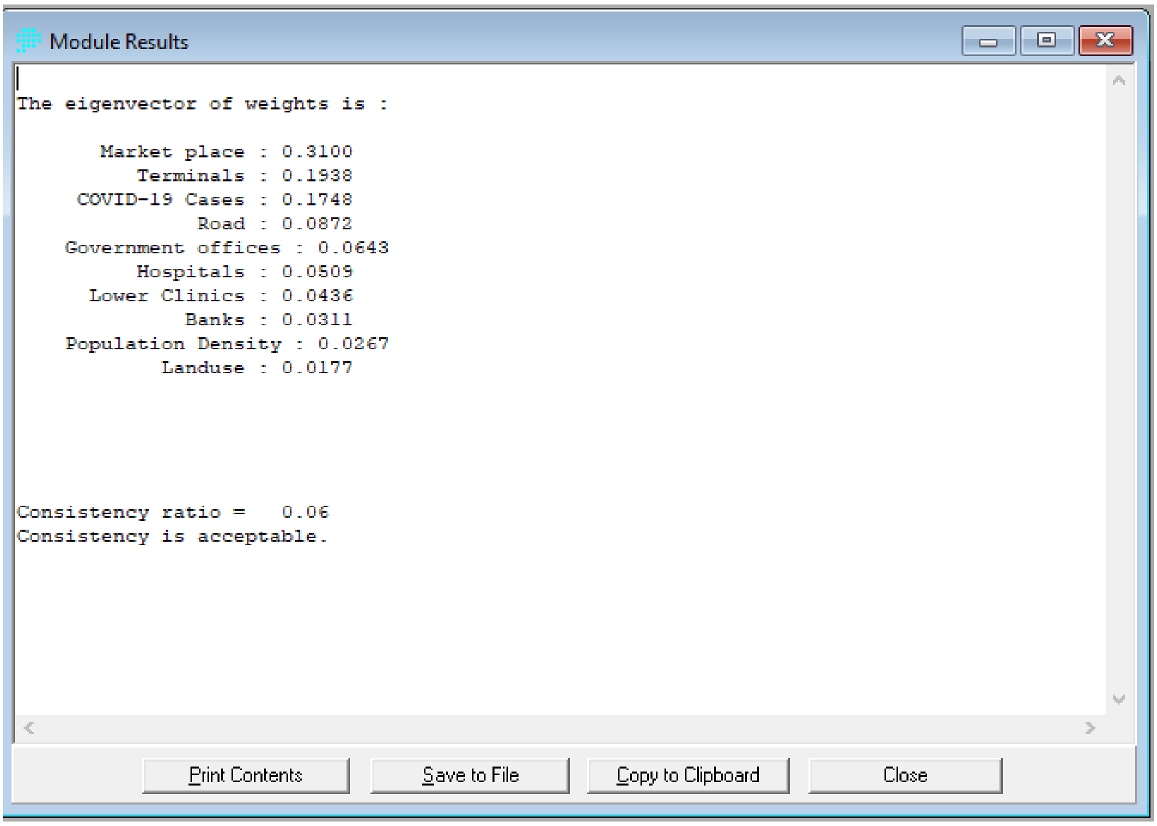
OBJECTID *	Shape *	Id	City	Sub_City	Covid_19_Cases	Woreda	Area	TIAMS	Shape_Length	Shape_Area
8	Polygon	0	Addis Ababa	Addis Ketema	8145	W03	893507.284494	Other	15407.737715	8638157.250498
1	Polygon	0	Addis Ababa	Akaki Kality	7491	W02	13020407.4505	Other	63830.408278	124232811.612828
9	Polygon	0	Addis Ababa	Arada	8098	W08	1077781.35981	Yes	18203.441123	9498472.500713
4	Polygon	0	Addis Ababa	Bole	28735	W12	23957307.4017	Yes	57589.977945	119637441.880686
3	Polygon	0	Addis Ababa	Colfe Keranio	14850	W02	6103258.90795	Yes	48921.25529	63401207.636491
10	Polygon	0	Addis Ababa	Gulele	10769	W04	748179.935921	Other	29483.358424	31190231.092012
5	Polygon	0	Addis Ababa	Kirkos	9715	W03	1321940.83095	Yes	18940.275638	14644935.807137
6	Polygon	0	Addis Ababa	Lideta	6874	W10	990459.255929	Other	17630.285015	9184173.238699
2	Polygon	0	Addis Ababa	Nifassilk Lafto	13690	W11	7192887.52154	Yes	44598.765881	58345321.379131
7	Polygon	0	Addis Ababa	Yeka	14232	W06	1010819.36335	Yes	48800.507865	82129212.038112

Appendix III: Study area's population number data collected from CSA

	2007			2020		
	Both sex	**Male**	**Femal**	**Both sex**	**Male**	**Femal**
ADDIS ABABA CITY ADMINISTRATION	**2,739,551**	**1,305,387**	**1,434,164**	**3,689,000**	**1,743,000**	**1,946,000**
AKAKI KALITY-SUB CITY	181,270	88,714	92,556	244,042	118,454	125,588
KEBELE 01/03	25,468	12,555	12,913	34,285	16,764	17,521
KEBELE 02/04	13,973	6,838	7,135	18,812	9,130	9,681
KEBELE 05/06	17,580	8,376	9,204	23,673	11,184	12,489
KEBELE 07/08/09	42,311	20,263	22,048	56,973	27,056	29,917
KEBELE 10/11	45,831	22,931	22,900	61,691	30,618	31,073
KEBELE 12/13	27,082	13,027	14,055	36,465	17,394	19,071
KILINITO,FECHE KOYE(17/18/19)	5,122	2,615	2,507	6,893	3,492	3,402
GELANGORA	3,903	2,109	1,794	5,250	2,816	2,434
NEFAS SILK-LAFTO-SUB CITY	316,283	148,984	167,299	425,935	198,929	227,006
KEBELE 03/04/05	34,846	16,089	18,757	46,934	21,483	25,451
KEBELE 06/07/08	40,364	19,140	21,224	54,355	25,556	28,799
KEBELE 09/14	33,529	15,698	17,831	45,155	20,961	24,195
KEBELE 10/18	41,299	19,560	21,739	55,615	26,117	29,497
KEBELE 12/13	28,023	12,806	15,217	37,747	17,099	20,648
KEBELE 16/17	36,081	17,447	18,634	48,580	23,296	25,284
KEBELE 01(HANA,LEBU,DERTU)	31,627	15,323	16,304	42,583	20,460	22,123
KEBELE 02	32,224	15,096	17,128	43,398	20,157	23,241
KEBELE 11	16,010	7,722	8,288	21,557	10,311	11,246
KEBELE 15	22,280	10,103	12,177	30,013	13,490	16,523
KOLFE KERANIYO-SUB CITY	428,895	207,641	221,254	577,467	277,250	300,217
KEBELE 02/03	32,866	15,731	17,135	44,255	21,005	23,250
KEBELE 01/05	76,076	35,088	40,988	102,467	46,851	55,616
KEBELE 08/09	40,714	20,752	19,962	54,795	27,709	27,086
KEBELE 10/11	51,498	26,246	25,252	69,309	35,045	34,264
KEBELE 13/14	37,962	18,557	19,405	51,108	24,778	26,330
KEBELE 15/16	43,999	20,983	23,016	59,247	28,017	31,230
KEBELE 06	41,751	19,000	22,751	56,240	25,369	30,871
KEBELE 07	35,621	17,844	17,777	47,947	23,826	24,121
KEBELE 12	13,034	6,497	6,537	17,545	8,675	8,870
KEBELE 04	55,374	26,943	28,431	74,553	35,975	38,578
GULELE-SUB CITY	267,624	129,396	138,228	360,334	172,774	187,560
KEBELE 01/02	20,932	10,361	10,571	28,178	13,834	14,344
KEBELE 03/04/05	28,124	13,247	14,877	37,874	17,688	20,186
KEBELE 07/17	24,495	12,208	12,287	32,973	16,301	16,672
KEBELE 08/16	37,066	17,605	19,461	49,913	23,507	26,406
KEBELE 09/15	31,954	14,877	17,077	43,036	19,864	23,172
KEBELE 10/11/12	32,704	15,481	17,223	44,040	20,671	23,370
KEBELE 13/14	23,727	11,335	12,392	31,949	15,135	16,815
KEBELE 19/20/21	29,235	14,045	15,190	39,365	18,753	20,611
KEBELE 06	13,264	6,106	7,158	17,866	8,153	9,713
KEBELE 10/18	26,123	14,131	11,992	35,140	18,868	16,272
LIDETA-SUB CITY	201,713	96,272	105,441	271,617	128,546	143,072
KEBELE 01/18	21,427	9,969	11,458	28,858	13,311	15,547
KEBELE 02/03	24,577	11,760	12,817	33,094	15,702	17,391
KEBELE 04/06	26,810	13,088	13,722	36,095	17,476	18,619
KEBELE 05/08	28,166	13,315	14,851	37,930	17,779	20,151
KEBELE 09/10	29,171	14,283	14,888	39,273	19,071	20,201
KEBELE 07/14	26,387	12,465	13,922	35,534	16,644	18,891
KEBELE 15/16/17	14,355	6,794	7,561	19,331	9,072	10,259
KEBELE 11	13,365	6,364	7,001	17,997	8,497	9,500
KEBELE 12	17,455	8,234	9,221	23,506	10,994	12,512
KIRKOS-SUB CITY	221,234	103,500	117,734	297,949	138,197	159,752
KEBELE 01/19	18,236	8,495	9,741	24,560	11,343	13,217
KEBELE 02/03	24,997	11,478	13,519	33,670	15,326	18,344
KEBELE 05/06/07	28,467	13,065	15,402	38,344	17,445	20,899
KEBELE 08/09	20,935	9,873	11,062	28,193	13,183	15,010
KEBELE 11/12	22,870	10,636	12,234	30,802	14,202	16,600
KEBELE 13/14	22,694	10,745	11,949	30,561	14,347	16,213
KEBELE 15/16	17,132	8,498	8,634	23,062	11,347	11,715
KEBELE 17/18	21,506	9,762	11,744	28,970	13,035	15,935
KEBELE 20/21	20,558	9,462	11,096	27,690	12,634	15,056
KEBELE 04	12,792	6,269	6,523	17,222	8,371	8,851
KEBELE 10	11,047	5,217	5,830	14,877	6,966	7,911

ARADA-SUB CITY	211,501	99,165	112,336	284,836	132,409	152,427
KEBELE 01/02	21,436	10,289	11,147	28,863	13,738	15,125
KEBELE 03/09	24,725	11,571	13,154	33,299	15,450	17,849
KEBELE 04/05	22,010	10,709	11,301	29,633	14,299	15,334
KEBELE 07/08	25,303	11,524	13,779	34,084	15,387	18,697
KEBELE 11/12	19,861	9,238	10,623	26,749	12,335	14,414
KEBELE 13/14	28,157	12,852	15,305	37,928	17,160	20,767
KEBELE 15/16	24,627	11,601	13,026	33,165	15,490	17,675
KEBELE 06	13,669	6,373	7,296	18,409	8,509	9,900
KEBELE 10	13,521	6,337	7,184	18,209	8,461	9,748
KEBELE 17	18,192	8,671	9,521	24,497	11,578	12,919
ADDIS KETEMA-SUB CITY	255,372	124,898	130,474	343,807	166,768	177,039
KEBELE 01/02/03	33,259	16,574	16,685	44,770	22,130	22,640
KEBELE 04/05	27,143	13,047	14,096	36,548	17,421	19,127
KEBELE 06/07	29,058	14,535	14,523	39,114	19,408	19,706
KEBELE 08/09/18	33,076	16,834	16,242	44,516	22,477	22,039
KEBELE 10/11/12	32,656	15,742	16,914	43,970	21,019	22,950
KEBELE 13/15	23,199	11,062	12,137	31,239	14,770	16,469
KEBELE 16/17	28,542	13,524	15,018	38,435	18,058	20,378
KEBELE 19/20	19,800	9,541	10,259	26,660	12,739	13,920
KEBELE 14/21	28,639	14,039	14,600	38,556	18,745	19,811
YEKA-SUB CITY	346,664	161,592	185,072	466,885	215,763	251,122
KEBELE 01/02	27,163	12,519	14,644	36,586	16,716	19,870
KEBELE 03/04	32,346	15,110	17,236	43,563	20,175	23,387
KEBELE 06/07	18,843	8,542	10,301	25,383	11,406	13,977
KEBELE 08/15	30,422	14,247	16,175	40,971	19,023	21,948
KEBELE 16/17/18	55,035	26,241	28,794	74,108	35,038	39,070
KEBELE 19	31,854	14,864	16,990	42,900	19,847	23,054
KEBELE 20/21	65,127	31,515	33,612	87,688	42,080	45,608
KEBELE 13/14	23,860	10,837	13,023	32,141	14,470	17,671
KEBELE 11/12	21,292	9,582	11,710	28,683	12,794	15,889
KEBELE 09/10	27,025	12,110	14,915	36,408	16,170	20,238
KEBELE 05	13,697	6,025	7,672	18,455	8,045	10,410
BOLE-SUB CITY	308,995	145,225	163,770	416,127	193,910	222,218
KEBELE 03/05	31,757	14,849	16,908	42,769	19,827	22,942
KEBELE 04/06/07	29,029	13,339	15,690	39,100	17,811	21,290
KEBELE 08/09	20,228	9,645	10,583	27,238	12,878	14,360
KEBELE 12/13	24,361	11,129	13,232	32,814	14,860	17,954
KEBELE 14/15	81,405	39,025	42,380	109,613	52,108	57,505
KEBELE 16/18/21/22	13,531	6,846	6,685	18,212	9,141	9,071
KEBELE 17/19/20	21,623	10,792	10,831	29,106	14,410	14,696
KEBELE 01	28,203	13,120	15,083	37,984	17,518	20,466
KEBELE 02	8,155	3,699	4,456	10,985	4,939	6,046
KEBELE 10	32,262	14,822	17,440	43,455	19,791	23,664
KEBELE 11	18,441	7,959	10,482	24,850	10,627	14,223

Appendix IV: Idrisi selva software weight output with Consistency ratio



Appendix V: Questionnaire format

Date ______________

Expert's profile

Professional title __________ Senior/intermediate/Junior, ________ Work Experience____

Expert Academic rank_____________________________

Questions

1. Based on your experience and prior knowledge please give rank (1-10) for COVID-19 infection risk vulnerability factors in Addis Ababa city as per their influence.
   a) Factors
      i. Land use ☐
      ii. Distance to marketplace ☐
      iii. Distance to road ☐
      iv. Distance to bank ☐
      v. Distance to hospital ☐
      vi. Distance to lower clinics ☐
      vii. Distance to terminals ☐
      viii. Number of COVID-19 positive case ☐
      ix. Distance to government office ☐
      x. Population density ☐
2. Please write if there are influential factors for vulnerability to COVID-19 infection risk in the study area that does not mentioned above?

   ____