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Environmental and Demographic Effects on Vector Borne Disease Incidence: Welfare Role on DHF Reduction

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Abstract

Many regions in developing countries are transitioning to an industrial economic model, accompanied by rapid population growth, which from one side is a welfare driver (WLF) and on the other side is a demographic pressure, especially a health problem such as vector-borne disease. The problem climaxes when this transition is always accompanied by environmental degradation (ENV), which begins with deforestation. *Objective:* [1] Determine the direct influence of: [1a] Demographic on DHF incidence, [1b] Demographic on Welfare improvement, [1c] Welfare on DHF incidence, [1d] Environment improvement on DHF incidence, [1e] Environment improvement on performance Welfare; and [2] The indirect influence of Welfare in mediating [2a] Demographic pressure and [2b] Environment improvement on DHF incidence. *Research Method:* Lampung Province was used as the research locus. Forest Resources Inventory Laboratory of Lampung University as a place for analysis. Postulate SEM (Structural Equation Model) was employed at a 95% confidence level. The endogenous variable was vector-borne disease (reflected by DHF incidence). The two exogenous variables were DMG (reflected by population density and the proportion of age of productive, industrial, and service workers) and ENV (reflected by maximum & minimum air temperature, forested areas, and other land uses). The mediating variable is WLF (reflected by poverty and HDI). *Findings:* [1] Directly, with a significant effect: [1a] DMG pressure increases DHF (P=0.000) and [1.b] WLF (P=0.000); [1.c] Environment improvement increases welfare (P=0.000) while [1d] reduces DHF; and [1.e] WLF improvement can reduce DHF (P=0.010) and [2] The role of WLF improvement [2a] can significantly reduce the incidence of DHF due to demographic pressure (P=0.007) while also [2b] amplifying environmental improvement in reducing DHF significantly (P=0.023). *Novelty:* To reduce DHF incidence, Welfare improvement can reverse the negative effects of Demographic pressure as well as act as an amplifier for the role of environmental improvement.

Keywords: Environmental; Land Cover; Global Warming; Reforestation; Structural Equation Modelling (SEM).

1. Introduction

Currently, many regions in developing countries are experiencing a structural transformation of the economy from a pattern that relies on the extraction of natural resources and agriculture to an industrial economy through agro-industrial stepping stones before becoming regions that rely on manufacturing and services industries. This transition

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process is generally accompanied by population growth, degradation of natural resources accompanied by an acute decline in environmental performance (ENV). This transition process can improve welfare through community participation in various economic sectors, reduce unemployment, increase income, reduce poverty, increase consumption, and increase access to secondary products and services.

This phenomenon is common in developing countries because it is triggered by low motivation to improve. It is true that many regions in the country have succeeded in achieving significant prosperity (WLF), but on the other hand, quite a few have had to make various forms of sacrifices that may be disproportionate. These victims can be in the form of demographic pressure and the depletion of natural resources, followed by acute environmental damage. Some demographic characteristics (DMG) are resources that can be relied upon to achieve prosperity, but some can also be a burden that can negate the level of welfare that has been achieved. This gap in income distribution between groups often creates marginalized communities, which are exploited by other groups due to poor institutional arrangements that regulate relationships between individuals in developing countries.

Environmental factors such as climate change and land use changes greatly influence the emergence or resurgence of various infectious diseases. The most sensitive diseases are those that are transmitted indirectly, meaning that they require transmission from host to host (such as diseases that spread through water and food) or an intermediate host or vector in their life cycle [1, 2]. When forests are converted into agricultural or urban land, the ecosystem and habitat of disease vectors such as the Aedes aegypti mosquito (which carries Dengue Hemorrhagic Fever) and Anopheles (which is a malaria vector) also undergo a transformation. Then this transformation can result in increased interactions between humans and disease vectors, thereby increasing the risk of disease spread.

Land use changes can negatively impact ecological integrity and biodiversity by disrupting the structure and function of food webs, altering terrestrial and aquatic biogeochemical cycles, altering ecosystem properties, introducing non-native species, including pathogens, and triggering infectious diseases in humans, domestic animals, and wildlife. Deforestation, expansion of grazing land, urbanization or sub-urbanization, infrastructure development (railways, highways, electricity networks), hydrological changes (dams, irrigation, canal construction), agricultural development (food crops, livestock), and extraction or depletion of natural resources (mining, logging, hunting) are all examples of land change [3, 4].

These changes have direct and indirect impacts on disease dynamics by influencing abundance, behavior, movement, immune responses, and contact between host and vector. Further research is needed to better understand this issue and identify knowledge gaps [4]. In addition, changes in land use also have the potential to influence rainfall patterns, drainage systems, and other environmental conditions that influence the development of disease vectors and the spread of disease itself.

Diseases spread by mosquitoes have been a serious problem for human and animal health worldwide for many years. Dengue Hemorrhagic Fever Dengue is an infectious disease that is still a health problem in Indonesia because it has the risk of causing death and spreads very quickly [5–7]. Efforts to control mosquitoes and reduce the transmission of the diseases they spread, such as malaria, yellow fever, and Dengue Hemorrhagic Fever, have been underway for a long time [8, 9]. However, these efforts are increasingly hampered by the impacts of changes in land use, climate change, urbanization, and the erosion of health systems, all of which contribute to the spread of mosquito-borne diseases [10].

The impact of changes in land use by humans has long been known as a factor in exacerbating diseases transmitted by mosquitoes. Some forms of habitat change have been well studied and documented, while the impacts of other human-induced environmental changes are only just being recognized or rediscovered. These changes can be grouped into several broad and overlapping categories, including water retention systems, deforestation, agricultural development, and urbanization. In addition to these changes, human behavior associated with each of these landscape modifications can contribute significantly to disease transmission. Reforestation efforts have the potential to influence the incidence of vector-borne diseases by restoring forest ecosystems that have been lost due to land use change. Restored forests can create an environment that is less suitable for disease vectors, thereby reducing contact between humans and these vectors [11].

Environmental factors, such as climate change and land use changes, along with demographic aspects, have a significant impact on the emergence of infectious diseases. The link between environmental changes, demographics, and the emergence of dengue fever is becoming increasingly clear. Demography, through changes in population structure, urbanization, and migration, can also influence patterns of infectious disease spread. Therefore, understanding the complexity of the relationship between humans, the environment, and demographic factors is key to developing dengue prevention and control strategies. In view of current globalization, community welfare has a crucial role, especially in the context of the spread of Dengue Hemorrhagic Fever (DHF). Community welfare, including economic and social conditions, is an important factor in determining the risk of dengue fever. Welfare not only reflects economic aspects but also plays an important role in the dynamics of infectious diseases as a result of environmental damage and demographic changes. The level of access to health, education, and sanitation facilities plays a key role in the spread of disease. Therefore, this research aims to explore the correlation between welfare levels, environmental factors, demographic dynamics, and the spread of dengue fever, with the hope of providing additional insights to support efforts to prevent and control this disease globally.

Aside from that, external environmental factors such as elevation, microclimate, particularly air temperature, sanitation, land use drainage, and so on all have a significant impact on vector-borne disease transmission. ation and changes in land use can be major causes of environmental change, including inland watery conditions and microclimate [12], a decline in ecological balance, the disappearance of natural enemies, the emergence of new mutants, and, in turn, an explosion in an area. disease outbreak [13]. In Lampung Province, one of the regions with an agro-industrial economic style, for example, according to Seno et al. (2018) [14], when there is deforestation of one percent in state forests, the incidence of DHF will increase by around 7.78 (Sd=4.52) while in community forests it will increase by 7.85 (Sd =4.15) incidence per 10 thousand population.

Deforestation with various accompanying impacts occurred in various regions of Indonesia, especially in the early 1970s [13]. However, according to Wulandari et al. (2021) [15] for Lampung Province, deforestation has actually been going on since the Dutch Colonization period, namely in 1905, when the first placement of migrants outside Java was designed as a supplier of laborers on various plantations. Climactic deforestation in this region due to forest encroachment when the authoritarian regime fell continued with decentralization of governance in the 1998–2004 period, as if there was no legal order in force [16]. It is acknowledged that the perpetrators of forest encroachment at that time were mostly marginalized community groups who did not become migrants and settled in urban areas, but their mobility from rural areas to urban areas and vice versa was also a determining factor in the spread and transmission of various diseases, including vector borne diseases.

Currently, the forested area in Lampung Province is only around 10% [13], of which the remaining 20% is generally in the form of coffee cultivation in agroforestry technical culture [15]. With such forest conditions, Lampung Province has placed Indonesia as the third-largest exporter of kpoi seeds in the world. But it has to be paid dearly with acute environmental degradation, high levels of poverty [17], and various prevalences of infectious diseases such as malaria [12], pulmonary TB [13], and DHF [14, 18].

Not only in Lampung Province, the ramification of problems between demographic potential and pressure, as well as environmental damage to welfare performance and the prevalence of vector-borne diseases such as DHF but is a common phenomenon that is often encountered in wet tropical developing countries. It is a shame that no researchers have yet been found who have published the results of their work that reveal the direct impact of demographic variables and environmental performance variables on the incidence of vector borne disease or on the level of welfare of the community. Apart from that, no researchers have yet revealed the indirect influence of demographic characteristics and environmental performance on the incidence of vector-born disease through the role of welfare performance variables. The research aims to: [1] determine the direct effect of: [1a] DMG on DHF incidence; [1b] DMG on WLF improvement; [1c] WLF on DHF incidence; [1d] ENV improvement on DHF incidence; [1e] ENV improvement on WLF performance; and [2] The indirect influence of WLF in mediating [2a] DMG pressure and [2b] ENV improvement on DHF incidence.

2. Material and Methods

This research was conducted in Lampung Province, Indonesia. The research location map is presented in Figure 1.

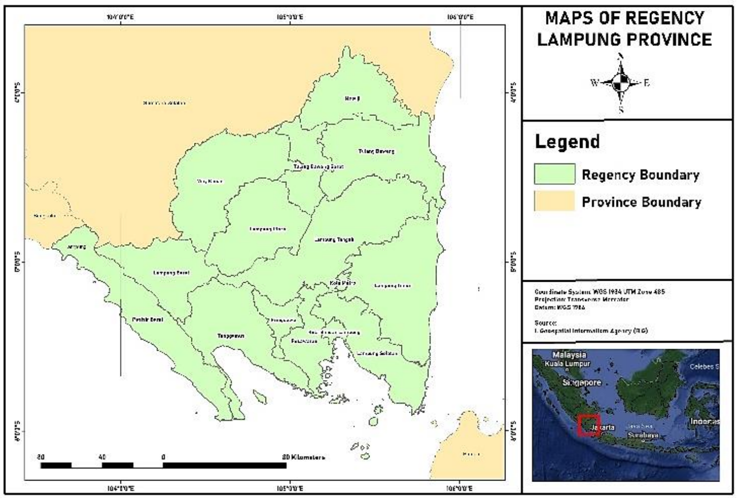

Figure 1. Research Location

2.1. Procedures

Procedures 1

Determining the dependent variable or dependent variable in this study is symbolized by the [Y] variable: Susceptibility to Dengue Hemorrhagic Fever Vector Infectious Disease per district/city in Lampung Province in 2009–2022. Data on disease morbidity rates are presented in units of incidence intensity per 10,000 population per year from 2009, 2012, 2015, 2018, 2021, and 2022 per district/city in Lampung Province, Indonesia. The independent variables, or independent variables, are [X1] Environmental Performance Variable, [X2] Demographic Variable, and [X3] Welfare Variable, which will later be analyzed using Structural Equation Modeling (SEM) Analysis.

Procedures 2

The Environmental Performance Variable [X2] consists of the indicators State Forest, Open Land, Open Field, Plantation, Settlement, Mixed Farming, Rice, Other Land, Maximum Temperature, Minimum Temperature, and Rainfall. So it is necessary to analyze changes in forest cover in Lampung Province between 2009, 2012, 2015, 2018, 2021, and 2022, requiring land cover maps for each year studied as well as other secondary data. Digital image processing is carried out through several stages, namely collecting land cover/use map data and then overlaying it using Geographic Information System (GIS) software. So a map of land cover/use changes in Lampung Province was produced.

Information regarding land cover is usually obtained through the results of satellite image classification, and the results of this classification are often used as a basis for research to analyze land use or land changes in an area. Land changes that occur in Lampung Province from year to year have significant implications for a number of diseases, such as malaria, dengue fever, and others. This research will focus on dengue fever, which is the main focus. The way Image Processing works is presented in Figure 2. The entire image processing procedure and research modeling are arranged as shown in Figure 3.

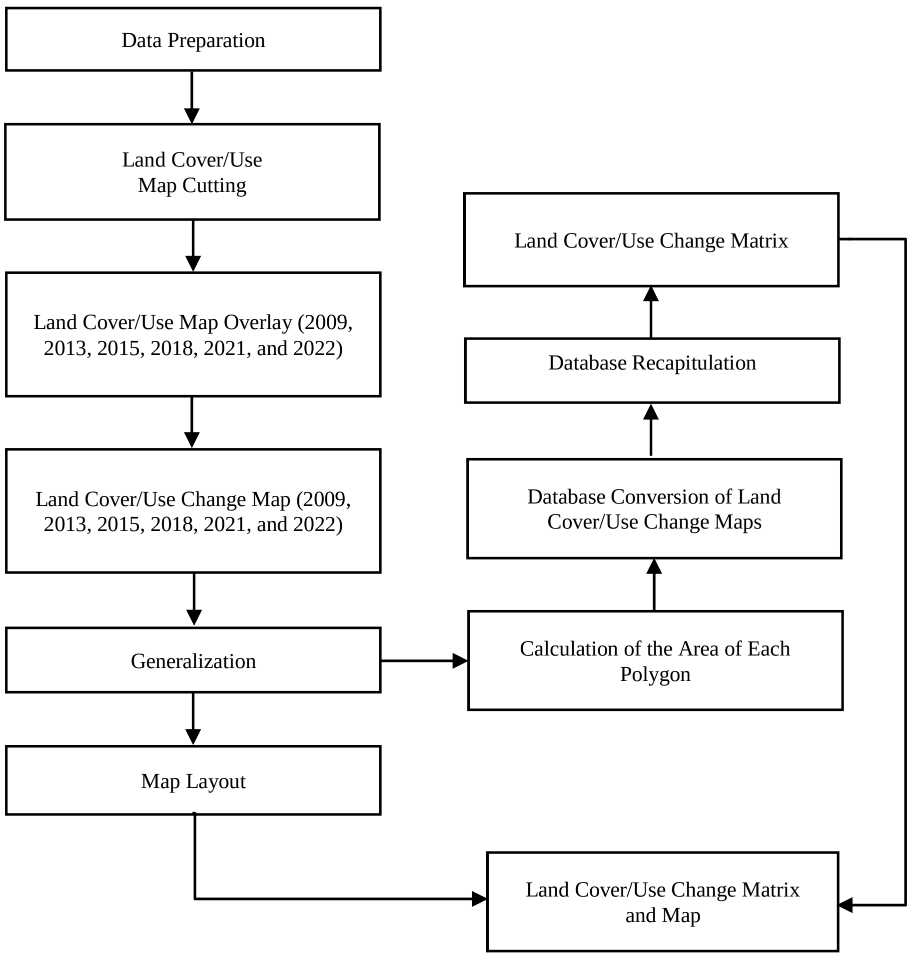

Figure 2. Image Processing Workflow (Land Cover Analysis)

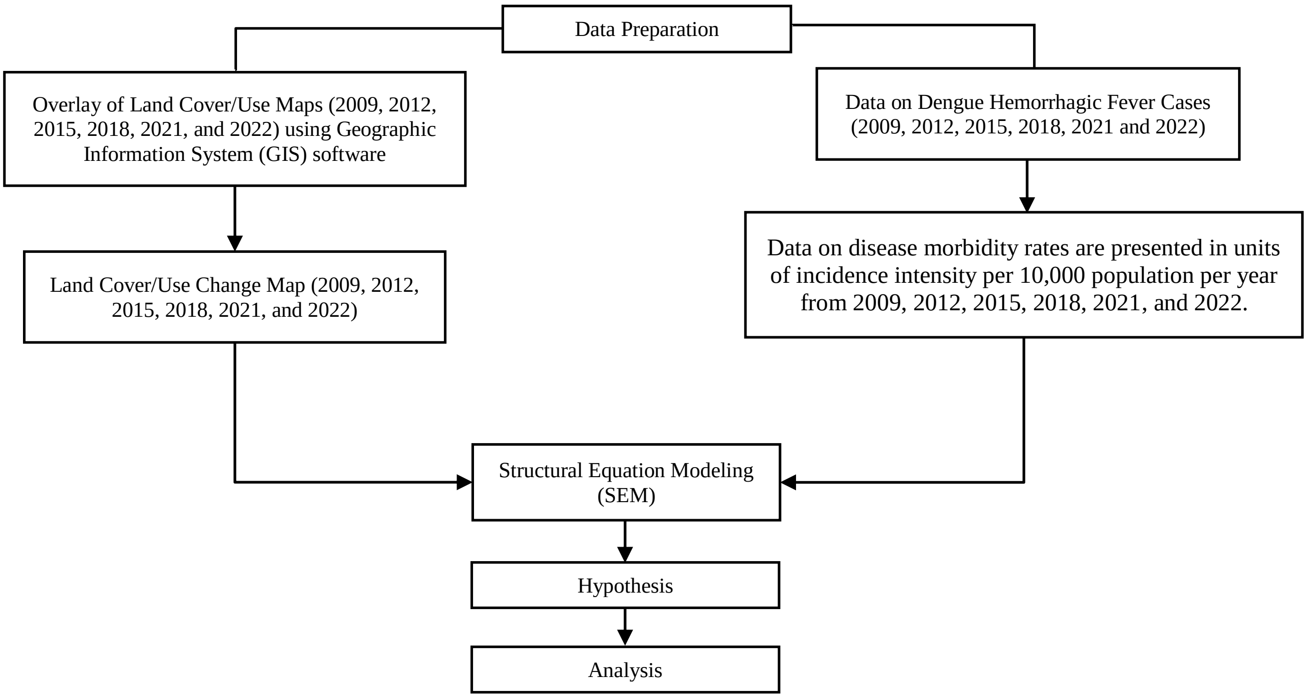

Figure 3. Overall Flow Diagram of Image Data Processing and SEM Modeling

2.2. Data Analysis

The data analysis used in this research is land cover analysis using Geographic Information System (GIS) software and quantitative analysis to determine the relationship between variables using Structural Equation Modeling (SEM) analysis via SmartPLS 4 software. SEM is an analysis technique that is stronger because it considers interaction modeling, non-linearity, and correlated independent variables [19, 20]. The general form of analysis in this research is connecting three independent variables [X1] Environmental Performance, [X2] Demography, [X3] Welfare with the dependent variable [Y] Susceptibility to Dengue Hemorrhagic Fever Vector Infectious Disease.

Structural Equation Modeling (SEM) Model Analysis Stages:

a. Overall model (*overall model fit analysis*)

b. Suitability of the measurement model (*measurement model fit analysis*)

c. Structural model fit (*structural model fit*)

The following are the variables, model symbols, score units and data sources which are presented in Table 1.

Table 1. Variables, indicators, and symbols in modeling

No	Latent Variable	
1	Environmental Performance [X1]	State_Forest Open_Field Plantation Settlement Mixed_Farming Rice Other Land Use Maximum_Temperature Minimum_Temperatur Rainfall
2	Demographics Chracteristic [X2]	Population_Density Productive_Age Industrial_Workers Service_Workers
3	Welfare Performance [X3]	Poverty Level HDI
4	Vector Borne Disease [Y]	Dengue Hemorrhagic Fever

The pattern of relationships between variables and indicators will be analyzed using Structural Equation Modeling (SEM) analysis which can be seen in Figure 4.

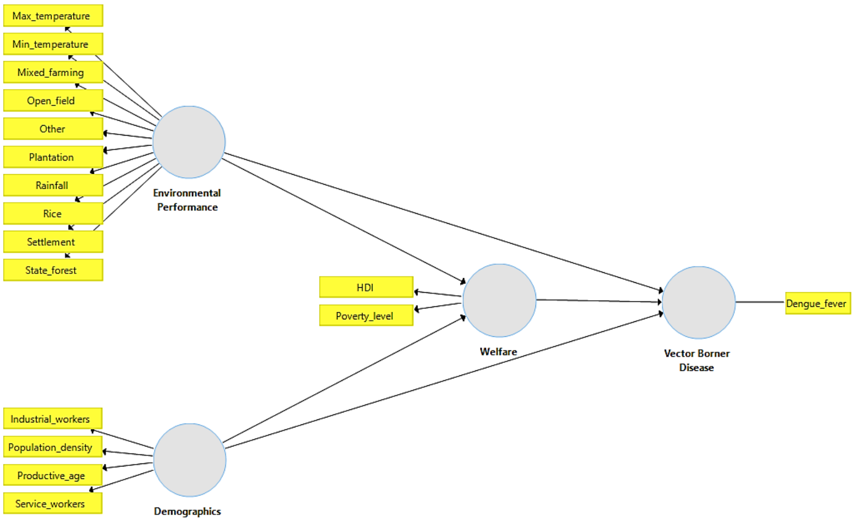

Figure 4. Structural Model of variable and indicator (Structural Equation Modeling Analysis)

3. Results

3.1. Land Cover

Data on land cover changes is very important for forest area management to determine planning and management strategies, as well as to improve forest monitoring [21]. Land use changes continue to occur along with the development process [22]. The land cover of a particular region can provide very important information for making policies to control environmental degradation at both the national and international levels [23].

The use of Landsat imagery is needed to identify district/city land cover in Lampung Province, which in the research was used in the 2009, 2012, 2015, 2018, and 2019 series (Figures 5 to 10). The land cover classes identified are state forests, community forests, vacant land, plantations, settlements, mixed agriculture, rice fields, and others. Changes in land use continue to occur along with the development process.

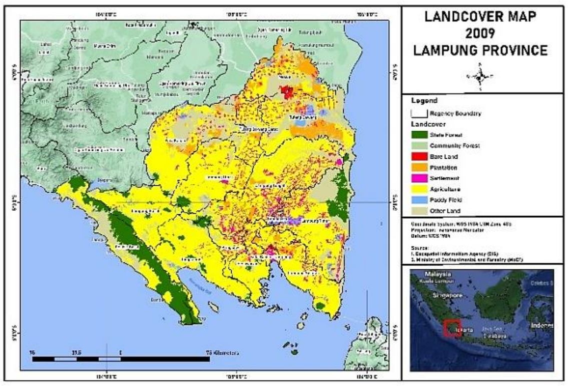

Figure 5. Land Cover in Lampung Province 2009

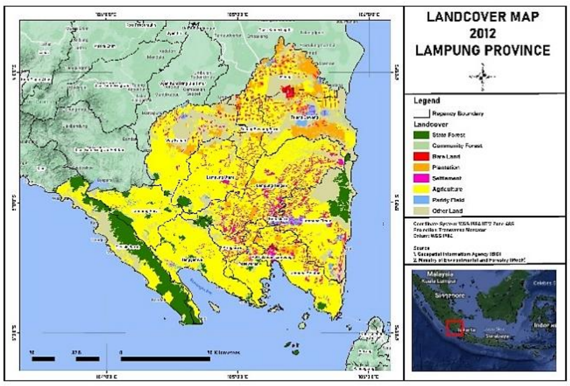

Figure 6. Land Cover in Lampung Province 2012

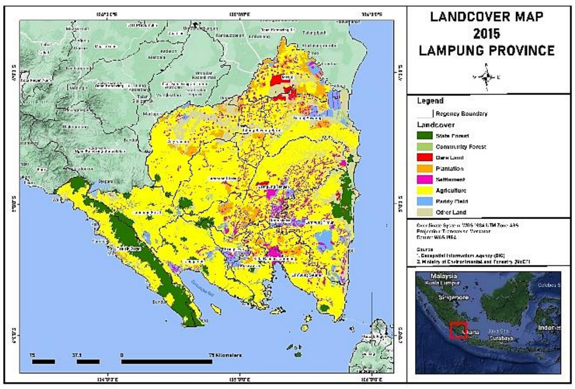

Figure 7. Land Cover in Lampung Province 2015

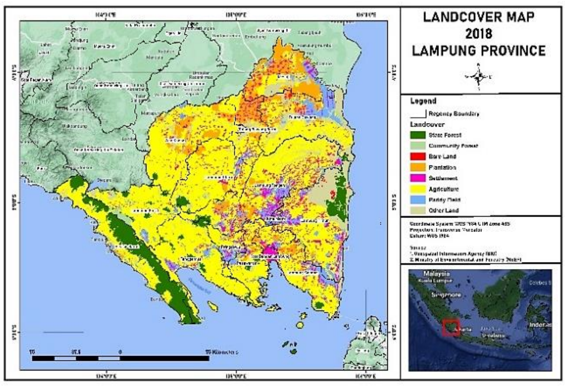

Figure 8. Land Cover in Lampung Province 2018

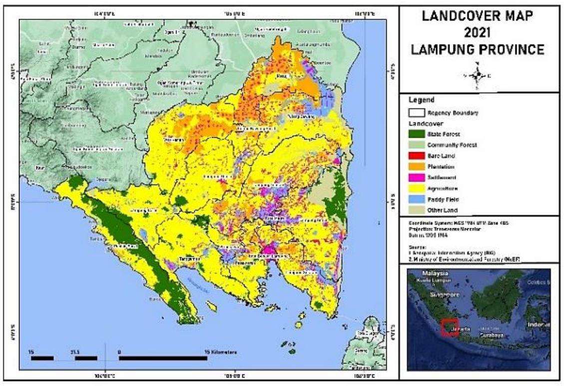

Figure 9. Land Cover in Lampung Province 2021

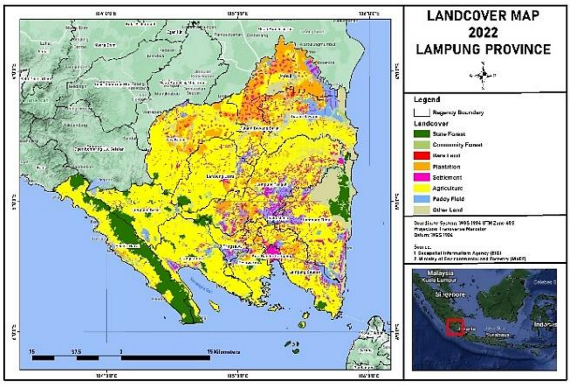

Figure 10. Land Cover in Lampung Province 2022

In the results of this research, the next stage of Structural Equation Modeling (SEM) analysis is carried out, divided into 3 stages, namely, overall model fit analysis, measurement model fit analysis, and structural model fit [24, 25].

3.2. Measurement Model Fit

Measurement model fit analysis aims to determine the validity and reliability of indicators; this step is also referred to as a two-step approach. If an indicator is found that has a value below 0.05, it will be removed.

When an indicator's loading factor is less than ≥0.70, it means that the indicator is valid enough to explain the other indicators for latent variables. Poor validity is indicated by the loading factor (λ) of 0.5 < λ < 0.5. Due to the large sample size in this investigation, indicators with a loading factor of less than 0.5 were employed to create the model. Which indicator is most important for explaining the latent variable can be seen based on the loading factor. The results in Table 1 show that all indicators meet the criteria and are declared significant.

Table 1. Loading factor of indicators

No	Variable	Indicator	Standardized Loading Factors (γ)	Description
1.	Environmental Performance [X1]	State_Forest	0.664	Significant
		Open_Field	0.712	Significant
		Plantation	0.752	Significant
		Settlement	0.697	Significant
		Mixed_Farming	0.583	Significant
		Rice	0.783	Significant
		Other Land Use	0.535	Significant
		Max.Temperature	0.747	Significant
		Min.Temperatur	0.562	Significant
		Rainfall	0.803	Significant
2.	Demographic Characteristics [X2]	Population_Density	0.710	Significant
		Productive_Age	0.700	Significant
		Industrial_Workers	0.621	Significant
		Service_Workers	0.838	Significant
3.	Welfare Performance [X3]	Poverty_Level	0.935	Significant
		HDI	0.764	Significant
4.	Vector Borne Disease [Y]	Dengue_Hemorrangic Fever Accidency	1.000	Significant

Table 2 shows that all research variables have Construct Validity and Reliability values with CR values above 0.70, AVE values above 0.50, and Cronbach's alpha values above 0.70, so they meet the criteria. Validity and reliability tests using AVE, CR, Cronbach's alpha, and HTMT values are important in SEM analysis because they provide an indication of the quality of the construct measurements used in the research. Validity measures the extent to which the indicators accurately reflect the construct being measured, while reliability measures the extent to which the indicators are consistent and reliable [26]. The AVE value describes how well the indicator variance is explained by the related construct, while CR and Cronbach's alpha measure the internal reliability of the indicator in measuring the construct.

Table 2. Construct reliability and validity

Latent Variables	Cronbach Alpha's	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Demographics Characteristic	0.792	0.707	0.811	0.521
Environmental Performance	0.875	0.883	0.899	0.576
Vector Borne Disease Incidence	1.000	1.000	1.000	1.000
Welfare Performance	0.753	0.812	0.842	0.729
Average				0.706

The magnitude of the direct influence of each variable is presented in the R-square measure (Table 3). The R-square value is the coefficient of determination for an endogenous construct or to determine the percentage of exogenous variables that are able to influence endogenous variables [27]. The R^2 value shows the amount of variation explained by the exogenous latent variable relative to the endogenous latent variable [28]. R^2 serves to describe the influence on predictor variables, the greater the number of constructs, the higher the R-square, and R^2 is always interpreted in complex model studies [29].

Table 3. R-Square (R^2)

Variable	R-Square	Description
Vector Borne Disease	0.684	Strong
Welfare	0.719	Strong
Average	0.701	Strong

3.3. Overall Model Fit Analysis – Goodness of Fit

The model suitability test using the Goodness of Fit Index (GoF) describes the overall suitability of the model, both for the outer model and for the inner model, and is calculated manually using the following formula [30].

$$Gof = \sqrt{Average\ AVE \times Average\ R^2}$$

The range of GoF Index values is divided into categories according to Tenenhaus et al. (2015) [31], as follows:

- The GoF value of 0.00-0.24 is suitable for the small category;
- The GoF value of 0.25-0.37 is suitable in the medium category;
- The GoF value of 0.38-1.00 is suitable for the high category.

Then the average R-Square value was obtained, namely 0.701, and the average AVE value was 0.706, resulting in a GoF value of 0.703. Information on overall model suitability, both from the outer model and inner model tests, is obtained through this GOF test. In the high suitability category, the model structure produced in this research is able to explain the conclusions of empirical facts well. Therefore, it can be concluded that, overall, the structural model formed in this research is valid and can be applied to the research location.

3.4. Structural Model Fit

The structural model can be seen through the coefficient test, namely by connecting latent variables. This test was carried out on each path, where in this study there were three paths that interconnected the latent variables. The outer loading coefficient numbers on the indicator arrows can be seen in Figure 11. The suitability of the following structural model can be seen in Table 4 structural model fit.

Table 4. Structural Model Fit: The Direct Effects

Path Hypothesis	Original Sample	Sample Mean	Standard Deviation	T-Values	P-Values
H_1: Demographics → Vector Borne Disease	1.331	1.336	0.092	14.428	0.000
H_2: Demographics → Welfare	0.473	0.458	0.080	5.912	0.000
H_3: Welfare → Vector Borne Disease	-0.324	-0.330	0.125	2.593	0.010
H_4: Environmental Performance → Vector Borne Disease	-0.468	-0.466	0.110	4.245	0.000
H_5: Environmental Performance → Welfare	0.429	0.466	0.091	4.690	0.000

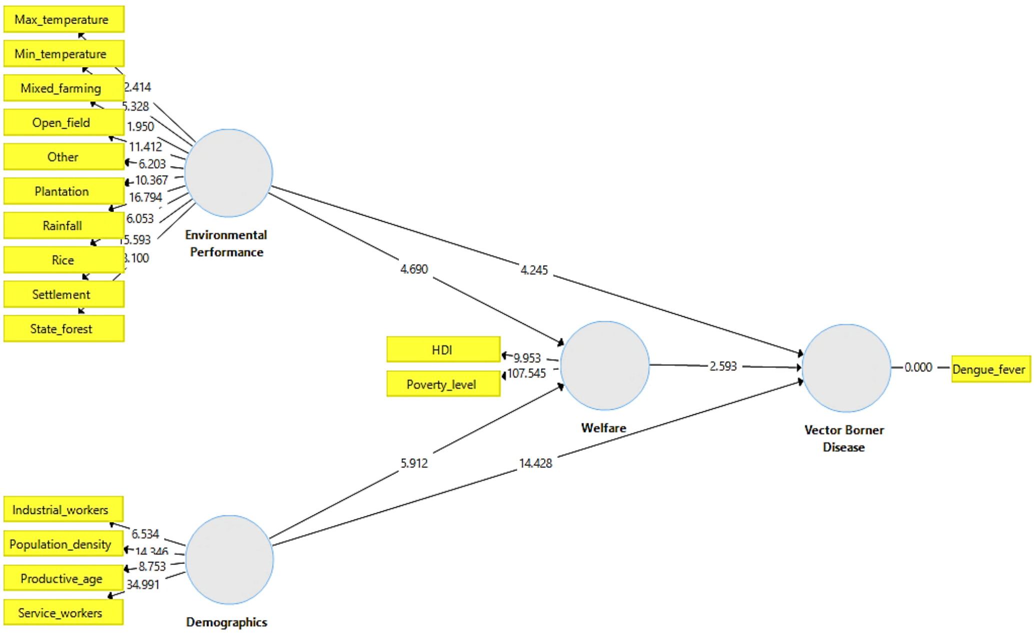

Figure 11. Outer Loading Coefficient Number on the Final Model Indicator Arrow

Structural models are built through identifying exogenous and endogenous variables to determine the influence of these variables and testing the model to determine the goodness of fit of the model to the observed data. Structural models are also used to examine hypothesis results about the influence or relationship between the variables being tested and provide empirical support for the theory or concept being tested. The results of hypothesis testing for the five hypotheses were proven to be significant with a p-value smaller than α (0.05) as follows:

H1: Demographic pressure significantly increases the risk of Vector Borne disease (p-values = 0.000);

H2: Demographic characteristics have a significant effect on welfare enhancement (p-values = 0.000);

H3: Welfare enhancement can significantly reduce vector born disease (p-values = 0.0010);

H4: Environmental improvement significantly reduces Vector Borne disease (p-values = 0.000);

H5: Environmental improvement has a significant effect on welfare enhancement (p-values = 0.000).

Table 5. Structural Model Fit: The Indirect Effects

Path Hypothesis	Original Sample	Sample Mean	Standard Deviation	T-Values	p-Values
H_6: Demographic → Welfare →Vector Borne Disease	-0.139	-0.136	0.051	2.727	0.007
H_7: Environment → Welfare →Vector Borne Disease	-0.153	-0.146	0.067	2.279	0.023

H6: Welfare improvement can significantly mediate the negative influence of demographics so that it can reduce the incidence of vector-borne disease (P=0.007).

H7: Welfare enhancement can significantly mediate the positive effects of environmental improvement so that the incidence of vector-borne disease is doubled (P=0.023).

4. Discussion

4.1. The Direct Impact of Demographics on Vector Borne Disease

We have to accept the H2: The demographic performance [DMG] affected the DHF incidence very significantly (P-value=0.000). Its sensitivity parameter is about 1.331 (Sd=0.092) which reflects that if other variables remain constant, the incidence of DHF will increase by around 1.331 per ten thousand population for every 1-unit increase [DMG]. All indicators from [DMG] are likely to cause an increase in [DHF] when its size increases, whether it is an increase in the number of productive age, the number of workers in the industrial sector, the service sector, or an increase in population density. It is a general understanding that DHF is a vector-borne disease that is heavily influenced by mobility. When someone is infected with the DHF virus and has great mobility, the opportunity to infect other individuals (via Aedes agepthy stings) will also increase. The mobility of people itself is also in line with the increase in the number of productive age populations. When productive age increases, people's activities outside the house also increase, which means that people's movements become more intensive, which also increases the chances of transmitting this vector-borne infection. Likewise, the number of workers in the modern sector, namely the industrial and service sectors, is increasing. These two sector workers actually have close, face-to-face and close proximity in working more intensively, which is much closer and more frequent than workers in traditional sectors such as agriculture, plantations, forestry or fisheries. If there are individuals who have been infected among workers in this sector, the chance of transmitting DHF will increase. The totality of all these indicators can actually also be reflected by population density, which can include and complement all three indicators.

Based on the output results of the Structural Equation Modeling analysis, the research results also state that the Demographics variable is significantly related to the Vector-borne disease (Dengue Hemorrhagic Fever) variable. There is an influence of Demographic dynamic variables, which include population density, productive age, industrial workers, and services workers on vector-borne disease (Dengue Hemorrhagic Fever). The existence of mosquito habitat supported by larval breeding sites, climatic conditions, and topographic and demographic characteristics indirectly influence transmission. Demographic factors have an important role in the spread of vector diseases. Human population growth and urbanization can create conditions more suitable for disease vectors, especially in densely populated settlements and lack of access to adequate sanitation facilities. Demographics can also influence the level of contact between individuals and population mobility, which can influence the spread of disease, and the level of well-being of people can influence their ability to protect themselves from vector diseases. Communities with limited access to health care, vaccination, or the use of insecticide-impregnated bed nets may be more susceptible to disease [32].

Mosquito-borne diseases have long been a major burden on human and animal health worldwide. There is a long history of mosquito control efforts to reduce the transmission of mosquito-borne diseases important for global public health, especially malaria, yellow fever, and Dengue Hemorrhagic Fever [8, 9]. However, these efforts are increasingly hampered by the combined impacts of land cover change, climate change, urbanization, and the erosion of health systems, all of which are implicated in the expansion of mosquito-borne diseases [10]. Population mobility is also a factor that can influence the incidence of dengue fever in an area. High mobility makes it easier for diseases to spread from one place to another. A person who has high mobility can transmit dengue fever in a new place, or vice versa, that person can contract dengue fever in that new place [33].

4.2. The Direct Impact of Demographics on Welfare

Demographic variables have a direct influence on welfare. In exploring the complexity of the relationship between welfare levels, demographic dynamics, and the spread of Dengue Hemorrhagic Fever (DHF), demographic variables become critical elements that have a direct impact on community welfare. There is an influence of Demographic variables which include population density, productive age, industrial workers, and service workers, on welfare. The demographic structure of society influences the level of interaction between individuals and population movement, which significantly influences the spread of disease. Social welfare also has an impact on individuals' capacity to protect themselves from disease vectors. Limited access to health care services, vaccinations, or the use of insecticide-treated bed nets can increase susceptibility to disease [32]. The age group most vulnerable to dengue fever are those under 15 years of age, who have a 1.2 times greater risk than those aged approximately 15 years. Age is one of the variables that influences the incidence of dengue fever, and low immunity makes children susceptible to dengue fever [34]. Industrial workers and service workers may have different levels of risk for vector-borne diseases. Industrial workers who work in environments that may have standing water or high vector densities may be at higher risk of diseases such as dengue fever. On the other hand, service workers who work outdoors or live in areas exposed to high vector risk may be at similar risk. Anthropogenic drivers currently known to cause the emergence and resurgence of Vector Borne Disease include demographic changes (e.g., global population movement and growth, unplanned and uncontrolled urbanization causing changes in vector dynamics) [35]. Dense human populations in built environments such as city centers, army barracks, and ships can facilitate contact between vectors and human hosts [36]. Community welfare is directly influenced by these demographic factors. Changes in the social and economic structure of society can form the basis for the spread of infectious diseases, such as dengue fever.

We do not have enough evidence to reject H2 that the composition or demographic characteristics of the study area can directly increase welfare [WLF] very significantly (P=0.000). The parameter sensitivity of [DMG] to [WLF] is about 0.473 (Sd=0.080). This means that if other variables remain constant, when there is an increase in [DMG] by one unit, [WLF] will increase by 0.473 units. The variable [DMG], which is reflected by the four variables (population density, proportion of productive age, and proportion of industrial and service workers), plays a very real role as a driver of welfare [WLF]. When the population increases, it also means increasing the intensity of various forms of relationships, which also means increasing various forms of transactions. There is no normal individual who can live in isolation and fulfill all his life needs alone. In fulfilling all these needs, in densely populated areas, as is usually the case in urban areas, the intensity of relationships between individuals is more intensive, the aspirations and life needs of each individual also increase and become more diverse, the production system also becomes more efficient, and the cost of living and transportation costs per unit also increase.

With this greater intensity of interaction, this region generates a lot of knowledge spillover over which triggers various kinds of innovation in production, distribution, and consumption systems. All of this will lead to increasing productivity, increasing the productivity of the economic system, reducing the cost of living, reducing poverty levels, while increasing consumption. This increase in consumption is the basis for improving health and increasing access to knowledge. These three composite increases are none other than HDI increases. Both the reduction in poverty levels and the increase in HDI are reflectors or indicators used in this research. An increase in the number of people of productive age also means an increase in the number and average of per capita income, as a trigger for reducing poverty rates as well as increasing HDI, starting from increasing consumption, health, and access to knowledge capital.

In fact, this level of knowledge capital is what drives innovation, efficiency, and increased productivity, which are important pillars for the sustainability of every civilization in the future. In addition, increasing the proportion of industrial sector workers can also cause economic productivity to become more efficient, especially for areas that are experiencing a transition in economic structure from an agrarian society to a manufacturing industrial economy through agroindustry, such as Lampung Province [37]. The greater the number of workers in the formal and modern sectors, the income will increase, poverty will decrease, and consumption will increase, accompanied by increased health performance. This will become the basis for accessing knowledge capital, which then becomes a source of innovation and the climax of [WLF].

4.3. The Direct Impact of Environmental Performance on Vector Borne Disease

Environmental performance variables on vector-borne disease (Dengue Hemorrhagic Fever) have a significant influence. Environmental factors include changes in land use that have been linked to disease transmission, specifically deforestation/forest fragmentation. habitat fragmentation, agricultural development/irrigation, followed by urbanization/suburbanization, livestock grazing, dam construction/water diversion, logging/extraction of natural resources, and land restoration [38]. Climate change, land use patterns, biodiversity, and socio-demographic structure (including urbanization) have influenced the geographic environment of vector-borne diseases. Climate change affects Dengue Hemorrhagic Fever. Based on estimates, global temperatures are expected to increase by an average of 1.0°C to 3.5°C by 2100. This will lead to an increase in the number of diseases carried by animals and the rate of disease transmission. Climate change will affect the spread of vector-borne diseases in the long and short term. In the short term, temperature and rainfall [39].

Climate change causes changes in rainfall, temperature, humidity, and air direction, thereby affecting health, especially the development of disease vectors such as the Aedes mosquito [40]. The reproduction of Aides Aegypty mosquito larvae which causes Dengue Hemorrhagic Fever (DHF), is influenced by climatic factors such as rainfall, temperature, and humidity. Apart from that, geographical factors such as the home environment are also one of the causes of Dengue Hemorrhagic Fever (DHF). Overcrowded housing and an unclean environment filled with water are breeding grounds for larvae. There are other risks, such as education and a lack of public knowledge regarding the symptoms of this disease, which also make them vulnerable to Dengue Hemorrhagic Fever (DHF). They consider daily body heat to be normal, so they are late in having their health checked [41].

Environmental factors and the role of the community in efforts to prevent dengue fever are closely related to the incidence of Dengue Hemorrhagic Fever in an area. Environmental factors that are related to the incidence of dengue fever consist of biological environmental factors (density of the Aedes aegypti mosquito vector and the presence of larvae), physical environmental factors (air temperature, humidity, lighting, mesh ventilation, and availability of lids on containers), and social environmental factors (population density, residential density, and support from health workers) [42].

As shown in Table 4, H3 must accept that increasing [WLF] very significantly (P=0.010) can reduce [DHF] with a parameter sensitivity of -0.324 (Sd= 0.125). This figure means that the incidence of DFH in the roping area will decrease by 0.324 people per 10 thousand population if welfare, or [WLF] increases by 1 unit. As stated previously, when poverty decreases, people's consumption levels also increase, which is then followed by an increase in health performance. In healthy individuals, physiological processes generally occur normally, which is followed by increased antibody function, which leads to increased resistance to various diseases, including vector-borne diseases such as [DHF], whose infection and transmission are very dependent on the performance of each individual's antibodies. Thus, it should be noted that the variable [DMG] on the one hand can increase the incidence of [DHF] as reflected by its three indicators (population density, proportion of productive age, and proportion of industrial workers and service workers), but on the other hand, it can also increase welfare, which leads to immunity and a reduction in incidence. It should also be noted here that infection and transmission of vector-borne diseases such as DHF not only depend on the level of individual immunity but also depend on the performance of the environment where the individual lives and does activities.

4.4. The Direct Impact of Environmental Performance on Welfare

We must accept that H4, namely [ENV], has a significant impact on vector-borne disease. As can be referenced in Table 4, the environmental performance variable [ENV] provides a parameter sensitivity of around -0.468 (Sd=0.11) for the incidence of DHF, meaning that if other variables remain constant, then every time there is an improvement in environmental performance of 1 unit, it will be followed by a reduction in the incidence of DHF. around 0.468 incidents per 10 thousand population. Seno et al. (2018) [14] reported that every 1% of deforestation in state forest areas and community forests can increase DHF levels by 7.782 (Sd=4.529) and 7.7875 (Sd=4.145) incidents per 10 thousand population, respectively, in Lampung Province. This increase is equivalent to an average economic loss of around USD 20 thousand in maintenance costs per 1% defect. Environmental services are intangible economic products, which can remind environmental care and management policy holders how important it is to control community behavior so that they do not carry out illegal logging and forest encroachment. Forested areas biophysically control the biodiversity conditions of each area. Increasing regional biodiversity performance through reforestation will maintain ecosystem balance, defend natural enemies, and suppress the occurrence of new disease mutants, which ultimately can reduce the prevalence of various diseases, including vector-borne diseases such as DHF.

In relation to reducing the incidence of DHF by increasing forested areas through reforestation, it is necessary to reveal its contribution from the perspective of individual humans who can host various kinds of diseases. Reforestation, as an effort to reverse environmental deterioration, can contribute various positive effects to public health. Reforestation can control microclimate stability by reducing maximum temperature increases and local extremes in air temperature, thereby providing a buffer against air temperature fluctuations at these two extremes. Reforestation can increase plant biomass production, improve air quality through O_2 production, and at the same time increase the C_2O absorption process of photosynthesis. In urban areas generally, reforestation is also able to improve air quality through absorbing or filtering particulate matter or other pollutant materials. Reforestation can also increase the beauty of the landscape, which can stimulate creativity. Local temperature stability, improved air quality, and increased beauty of the landscape will in turn increase environmental comfort for each individual in an area. In the end, this comfort can treat individual psychology, which is an important basis for the effectiveness of antibodies through the normality of each physiological function of each individual in this research area.

The environmental performance variable on welfare has a significant influence. Human behavior interacts with environmental factors to influence disease transmission. For example, modifications of the physical environment by humans can encourage the availability of vector breeding habitats [36]. Socio-economic changes (e.g., modern transport and trade, human encroachment on natural disease foci), and illegal activities. logging and livestock farming, illegal drug trafficking), accelerated exploitation of natural resources (e.g., land use change, forest degradation, decline in biodiversity, agricultural practices), changes in host susceptibility and adaptation of pathogens (e.g., increased movement of humans and animals, genetic variability of pathogens), degradation of public health infrastructure (e.g., lack of effective vector control, disease surveillance, and prevention programs), and climate change (e.g., changes in regional temperature and rainfall patterns causing changes in vector dynamics) [35].

Thus, changes in land use, high and low temperatures, and rainfall not only have an impact on the deterioration of the physical environment but also on the social and economic welfare of society. This impact can have an impact on society's vulnerability to vector-borne diseases such as Dengue Hemorrhagic Fever, considering that various factors such as access to health care, behavior, and economics are closely related to the spread of this disease.

4.5. The Direct Impact of Welfare on Vector-Borne Disease

As connected in Table 4, the H5 must be accepted, namely that [ENV] plays a very significant role (P=0.01) in [WLF] improvement. We have proven that in case no other variable changes, the [WLF] will improve around 0.429 (Sd=0.091) for every unit of [ENV] improvement. The proportion of forested area used as an indicator for [ENV] in this research, as stated previously, can be the main control for other indicators, including the performance of maximum temperature, minimum temperature, proportion of settlements, rice fields, and other land use in this research area. In this context, increasing each indicator for [ENV] can increase [WLF] both through improving the productivity of natural resources and human resources in the research area. Efforts to prevent deterioration [ENV] through reforestation, as previously stated, will be able to increase the productivity of the forest itself, both in the form of timber and non-timber products. Because they have long experienced deforestation since Dutch Colonization [15], this non-timber product in the research area has a large contribution to the community's economy, especially coffee beans planted under wood stands or agroforestry. NFTF from this research area is the 2nd contributor to Indonesia's coffee export volume and has for 3 decades placed Indonesia as the 3rd largest coffee exporter after Brazil and Vietnam [15].

Reforestation can also improve economic performance in downstream sectors, including plantations, food agriculture, fisheries, hydropower services, ecotourism services, and agro-industry sectors. Reforestation in upstream areas produces a lot of biomass, increases the supply of soil organic matter, increases soil water holding capacity, increases the soil's rainwater absorption capacity, suppresses the rate of soil erosion, maintains soil fertility, increases bellows ground diversity, and stimulates up ground diversity. Reforestation in the middle and downstream areas of the Lampung Province landscape (this research area) can reduce drought severity, flooding frequency, stabilize streamflow throughout the years, improve hydropower productivity, stabilize irrigation flow, enhance fishery productivity, cash crops, as well as food crops. Reforestation in state-owned forests in community forests by 1% can increase the aggregate income of the community in Lampung Province by USD 2.3 (0.35) and USD 1.1 (sd=0.38) million, respectively. Meanwhile, a 1% expansion of cash crop landscaping, lowland rice, and other food crops can increase community income by around USD 3.2 (0.51) million, USD 0.67 (0.36) million, and USD 0.08 (Sd=0.26) million, respectively. Increasing all indicators [ENV] through this reformation can further increase the income surplus in society, increase net exports of food ingredients, and stimulate the emergence of the agroindustry. According to Bakri et al. (2014) and Affandi (2009) [43, 44], the agro-industry sector has absorbed 77% of the workforce in Lampung Province in the last 45 years. The economic surplus in terms of primary natural resource productivity as the final impact of efforts to prevent deterioration [ENV] through reforestation can also be strengthened by improving the biophysical quality of the environment, as stated previously. The biophysical quality of the environment can support a comfortable work environment and increase the work productivity of each individual, which also increases income, reduces poverty, increases consumption, and leads to an increase in HDI.

The Welfare variable on vector-borne disease (Dengue Hemorrhagic Fever) has a significant influence. The Human Development Index reflects the level of social, economic, and health development in a region. Areas with a low Human Development Index may have poor health infrastructure, limited access to clean water, inadequate sanitation, and low education. All of this can exacerbate the risk and impact of Dengue Hemorrhagic Fever and malaria, especially because access to appropriate health care can be limited. Poverty levels can affect people's access to appropriate health care, diagnosis, and treatment. When access is limited, diseases such as dengue fever and malaria may go untreated or be treated too late, increasing their spread and severity.

Income is also included in the factors causing the occurrence of DHF. Low-income earners are at risk of death from dengue fever because people from the lower economic class mostly live in slum areas. They earn a living by relying on work as construction workers, junkyard workers, and drivers whose income is low, and they lack knowledge about the symptoms of dengue fever. They also consider body heat that lasts for days to be normal until the family is late in checking the family's health [41]. Recognizing that the populations most at risk are poor, illiterate, and distrustful of doctors, they view vector-borne diseases as a social ill and aim to empower poor rural communities and gain their trust. Rural schools and health centers were developed to educate people about mosquitoes and distribute quinine, thereby drastically reducing the incidence of malaria, illiteracy, and overall morbidity and mortality. Responses to vector-borne diseases produce solutions that broadly improve health and well-being [36].

Given the complexity of the interaction between the level of welfare, demographics, and environmental factors and the spread of infectious diseases such as Dengue Hemorrhagic Fever (DHF), it is necessary to understand that the level of community welfare has a significant influence on the spread of vector-borne diseases, including DHF. Welfare variables include economic and social aspects, and understanding their impact on vector-borne diseases is crucial in this context.

The level of community welfare plays a key role in determining the success of dengue prevention and control efforts. This variable not only reflects the community's ability to access health facilities but also influences economic factors that play a role in creating environmental conditions that support or harm the development of disease vectors such as dengue-carrying mosquitoes. Welfare variables can also provide an overview of the level of community knowledge and understanding of ways to prevent dengue fever, as well as their ability to overcome risk factors related to the surrounding environment.

4.6. The Indirect Effect of Demographic Characteristic on DHF through Welfare Improvement

As stated previously, research has proven that, on the one hand, demographic characteristics can directly increase the incidence of vector-borne diseases such as DHF. On the other hand, demographic characteristics can also directly improve performance [WLF], and by increasing performance [WLF], vector-borne diseases [DHF] can also be directly reduced. In this section, the role of [WLF] as a mediator variable in strengthening the decline in [DHF] is proven. As can be referred to in Table 5, H6 accepts that [WLF] can significantly lessen (P=0.023) the negative impact of [DMG] on the [DHF] incidence. If other variables remain constant, then for every 1 unit increase in [DMG], due to the role of [WLF], the incidence of [DHF] will be reduced by around 0.139 (Sd=0.051) per 10 thousand population. These findings illustrate the importance of increasing [WLF] when a region or country experiences population growth, especially for regions that are transitioning from an agrarian economy to an industrial economy, such as in this research area. In this transition process, environmental degradation and damage reach their peak, which will experience a turning point when per capita income is >USD 1250 per year (Wang, 2017). As an endogenous variable in every economic system, population, especially for the productive age segment, is a production factor determining the increase in aggregate community income, reducing unemployment and poverty rates, and a stimulator of improving consumption, which has implications for improving health, including immunity to vector-borne diseases such as DHF. The variable [DMG], thus, when it can increase [WLF], then the effect of increasing DHF through frequent interactions between individuals can be reduced significantly (P=0.023) through increasing immunity as an estuary of improving the performance of the productive age, increasing industrial and service workers in the region. this study.

4.7. The Indirect Effect of Environmental Improvement on DHF Incidence through Welfare Enhancement

The role of environmental enhancement in reducing DHF can also be amplified by welfare [WLF] improvement. As can be referenced in Table 4, directly improving environmental performance [ENV] can reduce the incidence of DHF and at the same time increase [WLF], which in turn can enhance welfare [WLF] and reduce the DHF incidence rate. Moreover, as can be referenced in Table 5, [WLF] enhancement can also be an amplificatory variable for the [ENV] variable in reducing the incidence of DHF. Through this intermediary [WLF], for every one unit increase in performance [ENV], the incidence of DHF will decrease by around 0.153 (Sd=0.146) per 10 thousand population. In this way, the influence of [ENV] directly or through the mediator [WLF] will result in a reduction in the incidence of DHF of around 0.621 incidents per 10 thousand population.

5. Conclusion

The results of this research are used to answer the research objectives, namely, to determine the direct influence of Demography on DHF incidence, Demography on Welfare improvement, Welfare on DHF incidence, Environment improvement on DHF incidence, Environment improvement on Welfare performance, and the indirect influence of welfare in mediating demographic pressure and environmental improvement on DHF incidence. The two exogenous variables were Demography (reflected by population density and the proportion of age of productive, industrial, and service workers) and ENV (reflected by maximum & minimum air temperature, forested areas, and other land uses). The mediating variable is Welfare (reflected by poverty and HDI). So it can be concluded that [1] directly has a significant effect: [1a] DMG pressure increases DHF (P=0.000) and [1.b] WLF (P=0.000); [1.c] Environment improvement increases welfare (P=0.000) while [1d] reduces DHF; and [1.e] WLF improvement can reduce DHF (P=0.010) and [2] The role of WLF improvement [2a] can significantly reduce the incidence of DHF due to demographic pressure (P=0.007) while also [2b] amplifying environmental improvement in reducing DHF significantly (P=0.023).

6. Declarations

6.1. Author Contributions

Conceptualization, S.B. and A.P.A.; methodology, S.B. and A.P.A.; software, A.P.A.; validation, S.B., A.P.A., E.K., and H.M.; formal analysis, S.B. and A.P.A.; investigation, S.B. and A.P.A.; resources, S.B.; data curation, S.B. and A.P.A.; writing—original draft preparation, S.B. and A.P.A.; writing—review and editing, S.B. and A.P.A.; visualization, S.B. and A.P.A.; supervision, S.B., A.P.A., E.K., and H.M. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

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6.5. Institutional Review Board Statement

Not applicable.

6.6. Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

6.7. Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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