*sustainability*

MDPI

*Article*

# Developing DPSIR Framework for Managing Climate Change in Urban Areas: A Case Study in Jakarta, Indonesia

**Yusuf Kristiadi [1,*], Riri Fitri Sari [2], Herdis Herdiansyah [1], Hayati Sari Hasibuan [1] and Tiong Hoo Lim [3]**

1 School of Environmental Science, Universitas Indonesia, Central Jakarta 10430, Indonesia
2 Faculty of Engineering, Universitas Indonesia, Depok 16424, Indonesia
3 Faculty of Engineering, Universiti Teknologi Brunei, Tungku Highway, Gadong, Bandar Seri Begawan BE1410, Brunei
* Correspondence: yusuf.kristiadi@ui.ac.id

check for updates

**Citation:** Kristiadi, Y.; Sari, R.F.; Herdiansyah, H.; Hasibuan, H.S.; Lim, T.H. Developing DPSIR Framework for Managing Climate Change in Urban Areas: A Case Study in Jakarta, Indonesia. *Sustainability* **2022**, *14*, 15773. https://doi.org/10.3390/su142315773

Academic Editors: Bing Xue, Jianhong (Cecilia) Xia, Dongqi Sun, Ye Wei, Zhi Qiao, Enxu Wang and Jun Yang

Received: 6 October 2022
Accepted: 24 November 2022
Published: 27 November 2022



**Abstract:** From an environmentally conscious and ecological perspective, the sustainability of cities within the effects of climate change are closely related to the wise use of resources and modifications in the ecological status of the environment. In terms of the ecological environment, the sustainability of smart cities entails meeting present and future societal demands for the environment of the water, land, and air, among others. Environmental and the ecological concerns that arise from rapid climate change and monetary developments are shown in the inconsistency between ecological assets, environmental pollution, and the destruction of nature. In this study, the authors aim to develop a strategy to deal with climate change in urban areas using Remote Sensing and the Driver-Pressure-State-Impact-Response (DPSIR) Framework with a case study in Jakarta Smart City. The DPSIR framework, which will be developed and implemented in the city of Jakarta, is a smarter and more sustainable framework that is evaluated through a systematic evaluation of sustainability with quantitative research using the entropy weight method and Partial Least Square-Structural Equation Modeling (PLS-SEM). These methods evaluate 58 representative elements of environments at the urban level, including the shortcomings of earlier research such as data availability, spatial and temporal constraints, and several related ecological indicators, such as soil pH, wind speed, air quality index as well as land changes in the spatial (spatiotemporal) time series. The results of the study show that in the metropolitan city of Jakarta, the *Drivers* that are related to climate change are the rate of population growth and the rate of industrial growth which, although increases people's income and GRDP in Jakarta; it also creates *Pressures*, namely an increase in the amount of water consumption and in the amount of wastewater. Based on these pressures, the environmental conditions (*State*) of Jakarta city have undergone several environmental changes, such as loss of water supply, changes in wind speed, changes in rainfall, and increasing concentrations of the Air Pollutant Standard Index. The *Impact* of these three elements resulted in the increase in household and industrial water consumption, an increase in annual electricity consumption, and deteriorating air quality. Hence, the *Response* to these four interrelated causal variables is that the Jakarta Provincial Government must increase annual funds for the construction of urban community facilities, increase the production capacity of clean water supply, build environment-friendly wastewater treatment facilities, increase the capacity of waste processing infrastructure and transportation fleets, and educate people to use water wisely to reduce the level of water use.

**Keywords:** framework strategy managing climate change; smart city; DPSIR; entropy; PLS-SEM

## 1. Introduction

Climate change, which is happening in the world today, is increasingly becoming a phenomenon discussed at the global level. This is due to the highly predictable impact of global warming on the universe. The condition of the world's forests as the main actor in absorbing gases that cause global warming, which has reached an alarming level, is a major factor in the increasing magnitude of climate change. However, the strategy of reducing the amount of greenhouse gases carried out in urban areas is considered no less important than efforts to improve forests [1,2].

Urban areas around the world in general have characteristics that make their inhabitants vulnerable to climate change. A lot of big cities are situated close to rivers, mountains, or seaside locations, making them vulnerable to climate change risks [3,4]. Urban areas generally always face the problem of urbanization which causes many environmental problems, such as lack of clean drinking water, rising temperatures and reduced precipitation, resulting in the suffering of the environment and people's lives due to these many negative effects.

One of the challenges faced by urban areas is that urbanization continues to increase. In 2015, more than half (54%) of the world's population resided in cities for the first time in human history. According to the United Nations survey on global urbanization trends, the urban population was only 39% in 1980. This urbanization trend continues, with the urban population estimated to make up 68% global population by 2050 [5]. In Asia, the urbanization trend also shows a similar increase, from 25% in 1980 to 47% in 2015. By 2050, 66% of the population will live in urban areas. In Indonesia alone, the urban population has reached 56.7% in 2020 [6], and according to a survey by the Citiasia Center for Smartnation (CCSN), this number will increase to 68% in 2035 [7].

Cities today, such as Jakarta, face environmental consequences of overpopulation and unplanned urban sprawl; however, they have a very important role in sustainable development strategies [8]. This aligns with the Sustainable Development Goals (SDG) number 11 of the 2015 UN Habitat Agenda in New York, which seeks to make cities more inclusive, resilient, and safe through the smart city program [9]. For a long time, the primary global paradigm has been for sustainable cities to respond to urbanization problems over the past three decades [10,11]. Not only sustainable but efficient and innovative cities with a comprehensive and integrated strategy must also answer the issues and impacts of urbanization and climate change [12]. Urbanization has caused many problems in Jakarta, among others; congestion, poverty, the emergence of squatters, waste that is not managed properly, floods, crime, pollution, and various other problems that occur in the city [13,14].

We discovered three key practical issues and gaps regarding urban sustainability evaluation studies after conducting a thorough literature review of the SDGs-G11 study: the absence of a comprehensive model for evaluating urban sustainability that can gauge its level; the driving forces behind urban sustainability development, such as a lack of institutions, robust data collection, and standards at the city level to support the evaluation model; and the lack of a comprehensive model for evaluating urban sustainability that can measure its impact [1,11,13,15–20].

In terms of climate change in general, there are complex problems with a variety of elements contributing to its development. Given these issues, a thorough and all-encompassing strategy is required for better comprehension and management of these issues [21]. Therefore, according to the objectives of SDG 13, a strategic framework is needed on how to address climate change in cities, especially in the form of setting priorities and goals, such as identifying and analyzing climate change risks and opportunities, assessing the level of climate risk in the city's vision and mission, risks, and opportunities for decreased emission targets [22]. Only then can we determine the actions and strategies we must take from the results of the analysis. There are at least two major points often associated with climate change efforts: mitigation and adaptation. These two processes must be carried out simultaneously so that they are well integrated; then, monitoring and evaluation are to be carried out [16].

Sustainability in cities is more closely linked to the efficient utilization of natural resources and changes in the ecological status of the environment from an ecological environmental perspective. To prepare societal needs in relation to water, land, air, and other surroundings both now and in the future, a smart sustainable city must address climate change in the ecological environment. Contradictions between environmental resources, environmental pollution, and environmental degradation are manifestations of the ecological environmental challenges brought on by rapid social development and economic progress [23]. To assess the performance of sustainable smart cities, many smart city indexes and frameworks have been proposed to support local government policymaking at the urban level. One of the very important objectives of evaluating the ecological environment is to achieve the Sustainable Development Goals (SDGs) in general, and to harmonize economic, social/community development, and the environment [17,24].

From the explanation above, it is necessary to measure the success parameters of smart cities in Indonesia, especially in Jakarta, and evaluating the performance of the city of Jakarta to become a sustainable smart city that is ready to face climate change which requires a smart city index and framework that supports sustainable local government policymaking at the urban level. To evaluate the sustainable development of urban areas, Carli (2018) suggested a multi-criteria decision-making method [25]. It is uncommon for indicator calculations in most urban size investigations, particularly in terms of data access, but the sustainable smart city index and framework are evaluated through interdisciplinary and multi-agency communication and cooperation [26].

By assembling an Integrated Ecological Environment Indicator using the DPSIR (Driver-Pressure-State-Impact-Response) framework, based on the above, Liu (2020) seeks to establish a sustainable smart city index and framework to complete the evaluation of urban environmental problems. According to the requirements for determining multi-dimensional, multi-thematic, and multi-urban indicators, this model is presented based on the Domain-Theme-Element three-level association mechanism and the DPSIR framework [15].

In this study, using the DPSIR framework mentioned above, the ecological environmental aspects in the last five years of conditions due to climate change in the city of Jakarta will be examined. Then, this DPSIR framework will become an environmental assessment of the last five years as a reference for strategies to control the impacts of climate change. Response can be used as feedback for Driver, Pressure, State, and Impact [27], and each feedback is different. Response addressed to Drivers is a form of Prevention. If they control the Pressure on the environment, this response will be Mitigation. Furthermore, if they can maintain the state of the environment, the form of response is Restoration. Finally, if they help overcome Impact, then the response is Adaptation. Hypothesis testing will also be carried out on ecological indicators such as wind speed, temperature, humidity, soil pH, air pollutant standard index, and rainfall, important factors of climate change and vegetation index, an important factor in carbon sequestration in urban areas, in this case the city of Jakarta.

## 2. Materials and Methods

### 2.1. Study Area

This research was conducted in the metropolitan city of Jakarta which is at the provincial level and is divided into five regions: Central Jakarta, North Jakarta, West Jakarta, East Jakarta, and South Jakarta, excluding the Kepulauan Seribu islands. It has an area of 662 km$^2$ and is passed by 13 rivers and their tributaries, all of which empty into the north of Jakarta as shown in Figure 1.

Jakarta Metropolitan City has the coordinates of $5°19'12''$–$6°23'54''$ LS $106°22'42''$–$106°58'18''$ east longitude. The northern boundary of Jakarta stretches along 32 km of coastline with 13 rivers, two canals and two flood lanes. Most of Jakarta is located below high tide. This condition means that some areas of Jakarta are more prone to flooding due to heavy rains and high tides.

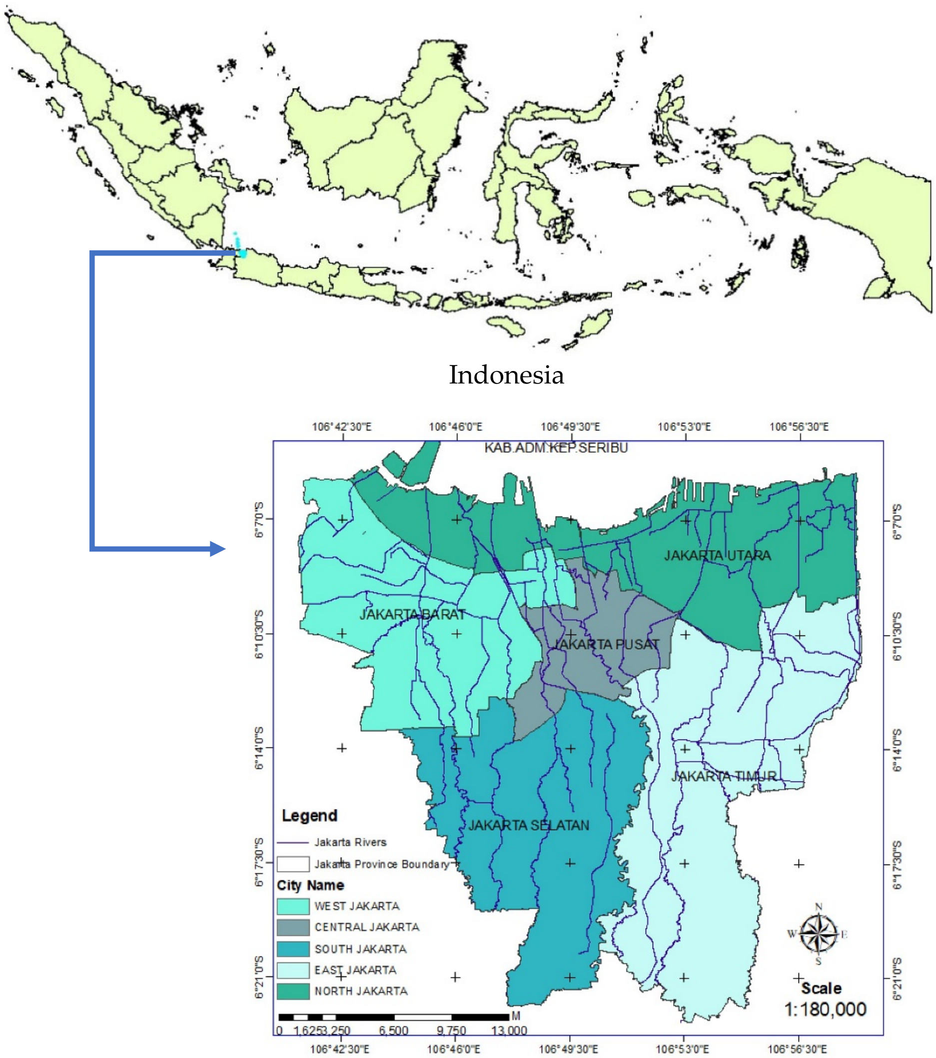


**Figure 1.** Research Area: Jakarta Metropolitan City, Indonesia.

The Province or Metropolitan City of Jakarta was chosen as a case study in this research because it is a big city and the current capital city, with a heavy burden of population growth, currently reaching 10,645,500 people. Moreover, it is also the center of livelihood for residents around the city of Jakarta who use public or private transportation every day, contributing to congestion in the city. Another thing to consider is that the Jakarta region is 662.33 km$^2$ and inhabited by 10,645,500 people. This means that the current Jakarta's density of people is 16.072 people/km$^2$. If the *Kepulauan Seribu* islands are not included in the calculation, then Jakarta's urban population density is at around 16,882 people/km$^2$, compared with only 141 persons per square kilometer living in Indonesia [28]. Complex problems, such as the level of urbanization, ecological problems, such as clean drinking water, air pollution levels, flooding problems, the quality of river raw materials that are also polluted, green open spaces and funds allocated for public purposes (public service obligations) that may be felt to be inappropriate or residents do not feel the benefits, made the city model quite representative if the findings of this research such as the model or framework found can be used and implemented later in other big cities in Indonesia, especially for models of evaluating and planning sustainable smart cities that look at problems holistically comprehensive in terms of environmental, economic, and social issues [19].

*2.2. Literature Study*

The literature review methodology used in this study is based on the division of research reports by Robert Yin and Yin (2009) using case study methods, including written reports and unwritten (oral) reports. Written records of classic single cases include books, reports, journal articles [29].

The report structure suggested by Yin (2009) in case study research includes: (1) Linear—analytic. This structure is the standard approach to creating research reports. The order of sub-topics includes the issues or problems studied, the methods used, the findings of the data collected and analyzed, and the conclusions and implications of the findings. (2) Comparative. In the comparative structure, repeat the same case study 2 (two) or more times by comparing the descriptive alternative or the same case explanation. The purpose of the repetition is to show the degree to which the facts fit each model. (3) Chronological. The type of approach in this structure is in a chronological order. The sequence of chapters or sections follows the beginning, middle and end of a case history. This structure plays an important role in carrying out explanatory case studies because the causal sequence must occur in a linear fashion. (4) Theory—building. In this structure, the sequence of chapters or sections follows the logic of theory development. The logic depends on the specific topic and theory. (5) Suspension. This structure runs counter to the analytical approach. The immediate results of a case study are paradoxically presented in the chapter or introductory section. The most contradictory part is presented in the development of the explanation of the results with alternative explanations considered in the next section. This type of structure is relevant for explanatory case studies. (6) Unsequenced. In this structure, the order of chapters or parts thereof, assumes no special importance. This structure is relevant for descriptive case studies. In the use of this non-sequential structure, researchers need to pay attention to the overall completeness test [29].

In research conducted by Salehi, et al. regarding climate change in Tehran, they applied the DPSIR model to conduct an analytical investigation of the variables affecting and influencing climate change, the city's resources and violated environmental boundaries. Tehran, geographically, is located on the southern slopes of the Alborz Mountains. It has a warm temperature and reasonably abundant water supplies, making it an ideal location position.

The DPSIR framework model is a framework for functional analysis that describes the causality in resolving environmental issues with a causal, systemic, and integrated framework that addresses the root causes of environmental issues, the connections between different environmental systems, and offers appropriate solutions [30]. In 1993, the Organization for Economic Cooperation and Development made its initial proposal for the DPSIR conceptual model [31]. It is common practice in sustainable development to analyze environmental issues and come up with solutions using the Driver-Pressure-State-Impact-Response (DPSIR) framework. In 1993, the Organization for Economic Cooperation and Development made the initial proposal for the DPSIR conceptual model. Numerous professionals have proposed preventive measures and useful ideas since 2003 to address the issues of sustainable development, the management of water and land resources, and the environment. Currently, the DPSIR framework is primarily used for decision-making and the application of environmental management science, as well as for the management and protection of water, soil, marine resources, and coastal creatures. So, this model aims to modify the previous DPSIR model, and gradually creating it into becoming an effective tool for solving environmental problems [32].

The DPSIR model is applied in all fields, such as the development of indicators, which makes it a model that builds and formulates policies. The DPSIR model describes the processes and relationships in the human system and its environment. This model consists of five elements that form a causal chain, namely the main driving force related to humans as a factor which causes environmental problems. These factors are usually related to socio-economic developments that require environmental resources. One of them is the exploitation of natural resources and the amount of waste that causes 'Pressure' on the environment and causes the 'State' of environmental parameters to change. These changes have detrimental consequences for human well-being and the balance of ecosystems. This led to a public 'Response' on how to find a solution. Responses render feedback to Triggers, Pressures, Circumstances, or Impacts. 'Responses' addressed to 'Driver' take the form of prevention. If the response controls the pressure on the environment, then the response will be in a form of mitigation response. Further, if the response is in the form of a restoration response to protecting the environment. Finally, Response can help overcome impacts, which in this case are adaptive responses [33].

Another study conducted by Jinhui Zhao et al., combines the peculiarities of the Yellow River Basin with important elements such as environmental factors and the overall socioeconomic system, where the DPSIR model framework is used to promote comprehensive high-quality green building in the Yellow River Basin of China. The DPSIR model is an enhancement of the framework evaluation system built to assess the environmental improvement in the Yellow River basin. The evaluation system is structured into four levels: layer targets, layer norms, layer elements, and indication layer, going from broad to specific, and general to specific. From this structure, five levels of driving forces, pressures, circumstances, impacts, and responses were compiled. Then, 12 representative elements were selected, and the actual objectives of green development were established by picking particular indicators at the level of indicators and creating a particular method for evaluating green development [34].

Development evaluation is carried out on improving the ecological environment after the construction of the 12 component indicator systems for environmental improvement in the Yellow Watershed has been completed. The enhancement of the natural environment is also influenced by several factors including the environment, economic situations, and resources. To reflect the actual status of environmental improvement level, the indicators used in the evaluation system should be weighted, and the processing method using the entropy weighting method ensures the evaluation is thorough, where the more information provided by the appropriate indicator, the greater its contribution to the achievement of the goals. As a result, using the weighted entropy approach is ideal for indicator weighing in the Yellow River Basin's green development system. The evaluation of environmental improvement indicators comprises five levels and is calculated using the Yellow River Quality Green Development Index. This is based on research on cognitive habits and the system's evaluation criteria for indicators. The level of development is indicated by a higher green. It is possible to evaluate the current state of development and provide recommendations for future growth by analyzing these green development evaluation indicators [34]. The methodology used to determine the Green Development Index (GDI) is as follows:

$$\mathrm{GDI} = \sum_{i=1}^{5} (x_i\, y_i) \quad (1)$$

In the formula, the $xi$ is the score for the five common layer components, and $y_i$ is how much each standard layer's component weighs. The National Bureau of Statistics provided the majority of the computation data, but it also used some information from the water resources bulletins for nine provinces in the basin and the statistics yearbook [34].

The other literature is the research conducted by Shi and Tong, who evaluats the spatial distribution pattern of ecological city development in 34 cities in China from 2011 to 2016. The data is also taken from statistical data from the China Statistical Yearbook, China City Statistical Yearbook, and others, and by also using the entropy method and the TOPSIS method which follow scientific, independent, operational, subjective, and objective principles combined into one. The method is demonstrated in a three-layer structure: criteria, key elements, and indexes. Research results generally show that the development of ecological cities in China shows a constant increase. However, cities with a high degree of coordination were still few in number [35,36].

In terms of a sustainable smart city, the research conducted by André Luis Azevedo Guedes et al., which identified the concept of a sustainable smart city, identified 20 potential smart city drivers. The survey was conducted on 807 professionals working in the related field and the results of the research identified seven drivers as the most important for increasing city intelligence in relation to sustainable smart city governance. Of the twenty drivers selected, fifteen focused mainly on city governance and five focused on technology. The seven drivers are urban planning, cities infrastructure, mobility, public safety, health, sustainability, and public policies, all of which are dominated by city governance rather than technology. Therefore, to deal with climate change for a sustainable smart city, it is better to refer to the seven driver focuses above [37].

Another study on smart buildings supporting smart cities conducted by Mariangela Monteiro Froufe et al. identified and linked the main drivers and smart building systems, by linking them to the main beneficiaries: users, owners, and the environment. Results show eleven drivers and eight systems which can be upgraded by more than one driver. Drivers from the user side are health, comfort, satisfaction, and security. Meanwhile, from the owner's perspective, the drivers are technology, integration, flexibility, and longevity. And lastly, from the environmental side, the drivers are ecology, energy, and efficiency [38].

The problem of climate change in a city in this study is investigated in a ceteris paribus framework for the global environment, meaning that the influence of the global environment is considered constant and does not directly affect urban environmental indicators.

Climate change itself is a symbol of a global problem, however, cities and their residents face the problem of climate change more specifically on a local level. Hence, this study does not directly include global and interrelated environmental influences ranging from heat waves, storms, coastal flooding to water scarcity, all of which put pressure on the infrastructure and social institutions of the residents of the metropolitan city of Jakarta. This is a prerequisite for similar research that may be mutually beneficial for further academic research that so far climate change represents urban areas that can be separated by fractions, because case studies of cities associated with climate change come from developed countries [39].

### *2.3. Data Collection Effect of Ecological Indicators*

In this research, the researcher collects secondary data from several sources such as Jakarta Province Statistical Data published by the Jakarta Provincial Central Statistics Agency from 2016 to 2021, and Clean Water Statistics, which was also published by the Jakarta Provincial Statistics Center from 2015–2021; Domestic Wastewater Management Strategy in Jakarta Province from the Electricity State Owned Company Jakarta Provincial Environment Service; Green Open Space Data from the Jakarta Parks and Cemetery Service; Final Report on Monitoring Groundwater Quality for Jakarta of 2020 Fiscal Year by the Jakarta Provincial Environment Bureau; Annual Report of the Deputy Governor for Spatial Planning and Environment 2018–2021; Official Gazette of Jakarta Province Statistics 2016–2022; Environmental Monitoring Report of Jakarta River Water Quality for Fiscal Year 2020 by the Environmental Service of Jakarta Province; 2020 Jakarta Provincial Fiscal Study, Report of Water Pollution Problem in the Jakarta Region from the Regional Environmental Supervisory Agency of Jakarta Province; Data from the Jakarta Regional Environmental Laboratory; Jakarta Rises a New Face of Jakarta 2021; 2019 Sustainable Development Goals Indicators for the province of Jakarta; Data from the Meteorology, Climatology and Geophysics Agency 2016–2021; Data Electricity State Owned Company Distribution of Jakarta and Tangerang; Journal of the Need for Green Open Space by Sri Pare Eni (2015); Teaching Staff of the Department of Architecture, Indonesian Christian University; the latest scientific publications journals related to environmental and environmental ecology issues of Jakarta province and other sources from the portal of the local government; the Agency for the Assessment and Application of Technology, and the Ministry of Environment and Forestry. The researchers summarized these data in Table 1. Table of Secondary Data and Vegetation Index Data to be Processed with the Entropy Method in the DPSIR Framework.

**Table 1.** Secondary Data and Vegetation Index Data for Processing in the DPSIR Framework.

| | | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|
| **Driver** | | | | | | | |
| D1 | Total population | 10,277,628 | 10,374,200 | 10,467,630 | 10,557,810 | 10,562,090 | 10,645,500 |
| D2 | Population growth rate | 0.98 | 1.1 | 1.07 | 1.19 | 0.92 | 1.01 |
| D3 | Urbanization rate | 2.87% | 2.89% | 2.91% | 2.93% | 2.94% | 2.90% |
| D4 | Population income per capita | 227,230,000 | 246,960,000 | 268,320,000 | 253,099,254 | 266,790,000 | 260,400,000 |
| D5 | Gross Regional Domestic Product | $2{,}159{,}070 \times 10^6$ | $2{,}365{,}350 \times 10^6$ | $2{,}599{,}330 \times 10^6$ | $2{,}849{,}830 \times 10^6$ | $2{,}159{,}070 \times 10^6$ | $2{,}159{,}070 \times 10^6$ |
| D6 | Jakarta's GDP growth rate | 5.87 | 6.20 | 6.17 | 5.82 | −2.34 | 4.10 |
| D7 | Industry growth rate | 6.59 | 6.96 | 6.93 | 6.54 | −2.63 | 7.07 |
| D8 | Adequate drinking water source | 3 | 3 | 3 | 3 | 3 | 3 |
| D9 | Drinking Water Raw Water | 7,162,434,550 | 7,162,434,550 | 7,162,434,550 | 7,162,434,550 | 7,162,434,550 | 7,162,434,550 |
| D10 | Clean Drinking Water Production | 594,797,102 | 613,254,707 | 622,911,977 | 631,957,813 | 634,519,000 | 634,519,000 |
| D11 | Land area of Jakarta province = km$^2$ | 662.33 | 662.33 | 662.33 | 662.33 | 662.33 | 662.33 |
| **Pressure** | | | | | | | |
| P1 | Population density per km$^2$ | 15,517 | 15,663 | 15,804 | 15,940 | 15,970 | 16,073 |
| P2 | Number of clean drinking water customers | 839,391 | 851,155 | 863,165 | 878,268 | 896,782 | 896,782 |
| P3 | Number of Gas customers | 13,472 | 13,827 | 13,827 | 13,827 | 13,827 | 13,827 |
| P4 | Gas Usage Ratio | 0.13% | 0.13% | 0.13% | 0.13% | 0.13% | 0.13% |
| P5 | Water consumption per capita | 401.65 | 401.34 | 407.82 | 412.89 | 551.44 | 551.44 |
| P6 | Amount of water consumption | 337,140,611 | 341,601,198 | 352,013,192 | 362,626,303 | 494,518,000 | 494,518,000 |
| P7 | Annual amount of wastewater (m$^3$/year) | 1,189,094,646 | 1,231,982,087 | 1,274,869,528 | 1,317,756,969 | 1,360,644,410 | 1,403,531,851 |
| P8 | Number of Industries | 1323 | 1323 | 1323 | 1323 | 1323 | 1323 |
| P9 | Road surface length | 6280.81 | 6652.68 | 6652.68 | 6652.68 | 6652.68 | 6652.68 |
| P10 | Green open area | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 |
| P11 | Quantity of Gas Sold | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 |
| P12 | Number of electricity customers | 4,000,000 | 4,205,365 | 4,395,066 | 4,583,706 | 4,755,494 | 4,755,494 |
| **State** | | | | | | | |
| S1 | Average total water resources | 594,797,102 | 613,254,707 | 622,911,977 | 631,957,813 | 634,519,000 | 634,519,000 |
| S2 | Amount of Surface Water Supply | 594,797,102 | 613,254,707 | 622,911,977 | 631,957,813 | 634,519,000 | 634,519,000 |
| S3 | Amount of Groundwater Supply | 9,143,484 | 9,143,484 | 9,143,484 | 9,143,484 | 9,143,484 | 9,143,484 |
| S4 | Loss of water supply | 257,656,491 | 271,653,509 | 270,898,785 | 269,331,510 | 140,001,000 | 140,001,000 |

**Table 1.** *Cont.*

| | | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|
| S5 | Water consumption of the population per capita | 401.65 | 401.34 | 407.82 | 412.89 | 551.44 | 551.44 |
| S6 | Residential waste discharge | 2,320,394 | 2,393,345 | 2,466,297 | 2,539,248 | 2,612,199 | 2,685,151 |
| S7 | Industrial waste | 361,775 | 379,298 | 396,822 | 414,346 | 431,870 | 449,394 |
| S8 | Green open space | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 |
| S9 | Green open space ratio | 9.98% | 9.98% | 9.98% | 9.98% | 9.98% | 9.98% |
| S10 | Annual average concentration of Air Pollutant Standards Index | 71.21 | 70.01 | 89.45 | 57.74 | 54.53 | 82.26 |
| S11 | Wind velocity | 1.70 | 1.79 | 3.50 | 2.00 | 1.49 | 1.50 |
| S12 | Temperature | 28.60 | 28.55 | 28.70 | 28.55 | 28.80 | 29.80 |
| S13 | Humidity | 77.75 | 74.50 | 74.00 | 73.88 | 76.00 | 76.00 |
| S14 | Rainfall ($mm^2$) | 2366 | 2061 | 1524 | 1615 | 2832 | 1043 |
| S15 | Soil pH | 7.09 | 7.09 | 7.09 | 7.09 | 7.09 | 7.09 |
| S16 | Spatiotemporal NDVI (Vegetation Index) | 186.369 | 186.369 | 217.770 | 169.344 | 177.908 | 182.783 |
| **Impact** | | | | | | | |
| I1 | Industrial water consumption per capita | 590.66 | 599.39 | 633.71 | 964.20 | 793.49 | 793.49 |
| I2 | Number of Industrial Water Customers | 117,089 | 119,788 | 117,089 | 128,886 | 129,516 | 129,516 |
| I3 | Industrial water consumption | 69,160,000 | 71,800,000 | 74,200,000 | 124,272,000 | 102,770,000 | 102,770,000 |
| I4 | Household water consumption | 188,640,000 | 189,210,000 | 191,870,000 | 237,038,000 | 240,813,000 | 240,813,000 |
| I5 | Water supply quantity | 594,797,102 | 613,254,707 | 622,911,977 | 631,957,813 | 634,519,000 | 634,519,000 |
| I6 | Green coverage area | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 | 66.10 |
| I7 | Air quality level | 71.21 | 70.01 | 89.45 | 57.74 | 54.53 | 82.26 |
| I8 | Amount of household gas | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 | 982,886,312 |
| I9 | Annual electricity consumption (Wh) | 41,327,631,069 | 31,643,135,773 | 32,779,195,892 | 34,107,978,071 | 32,194,867,748 | 32,194,867,748 |
| **Response** | | | | | | | |
| R1 | Water usage rate | 451,610,000 | 494,295,000 | 499,301,000 | 511,855,000 | 494,518,000 | 494,518,000 |
| R2 | Water supply production capacity | 561,763,000 | 543,534,000 | 634,195,000 | 553,518,000 | 634,519,000 | 634,519,000 |
| R3 | Water supply pipe | 11,916 | 11,916 | 11,916 | 11,916 | 11,916 | 11,916 |
| R4 | Wastewater treatment rate | 3% | 3% | 3% | 3% | 3% | 3% |
| R5 | Volume of treated wastewater | 80,465.06 | 83,179.31 | 85,893.57 | 88,607.83 | 91,322.09 | 94,036.34 |

**Table 1.** *Cont.*

| | | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|
| R6 | Green coverage ratio | 9.98% | 9.98% | 9.98% | 9.98% | 9.98% | 9.98% |
| R7 | Gas coverage ratio | 0.13% | 0.13% | 0.13% | 0.13% | 0.13% | 0.13% |
| R8 | Domestic waste collected and transported (tons/day) | 6,562 | 6,975 | 7,453 | 7,702 | 7,424 | 7,424 |
| R9 | Number of latrines (goose neck) | 2,717,544 | 2,717,544 | 2,717,544 | 2,717,544 | 2,717,544 | 2,717,544 |
| R10 | Annual fund for the construction of urban community facilities -PSO (trillion) | 1.60 | 2.80 | 3.27 | 3.27 | 3.27 | 3.27 |

(Source: Processed by Researchers, 2022).

In this study, the researchers added to the lack of data on the weaknesses of previous studies, such as several related ecological indicators such as wind velocity and soil pH [15], and the researchers added other ecological indicators, namely: the annual average concentration of Air Pollutant Standards, temperature, humidity, and precipitation. Air Pollutant Standards is determined based on 7 main parameters, namely: Carbon Monoxide (CO), Sulfur Dioxide (SO2), Nitrogen Dioxide (NO2), and Particulates (PM10 and PM2.5), Ozone (O3), and Hydrocarbons (HC) [18].

### *2.4. Data Collection for Calculating Vegetation Index*

The data for calculating the vegetation index was carried out by research observations that directly observed the objects of the Jakarta province area using remote sensing. In this research, researchers took data from Sentinel-2 at https://earthexplorer.usgs.gov/ (accessed on 24 August 2021). Sentinel-2 is composed of 2 (two) constellation satellites. Sentinel2-A and Sentinel-2B, which were launched in 2015 and 2017, respectively. Although both were launched at separate times in the same orbit. Sentinel-2 has 13 bands with a 10 m RGB resolution, better than the Landsat satellite which has 15m RGB [18,40].

Here are the steps to obtain the Vegetation Index value using the NDVI (Normalized Difference Vegetation Index) method [41]:

1. The first step is to download remote sensing satellite image data from Data Sentinel2-A [42]. The researcher takes it with the address Jakarta, latitude: −6.2088 and longitude: 106.8456, taken within the annual deadline: 2017, 2018, 2019, 2020, and 2021 with additional criteria, namely the Cloud Cover, which is below 10% so that the cloud cover is at least minimal.

2. From the Sentinel2-A satellite image data obtained from the https://eartheexplorer.usgs.gov/page (accessed on 24 August 2021), the researchers then processed the image data using ArcGIS Desktop 10.8 software, and the processed files were files with band 8 and band 4 and calculated with the NDVI formula [43,44].

$$\mathrm{NDVI} = \frac{Nir - Red}{Nir + Red} \tag{2}$$

where NDVI: Normalization Difference Vegetation Index; *Nir*: Band 8; *Red*: Band 4.

The raster file was clipped to be limited in area to the Jakarta province with the Jakarta Regional Boundary file in SHP (Shapefile) format.

3. The results of data processing using the NDVI formula are apparent in Figure 2. The NDVI Map of Jakarta Province in 2017 can be seen Figure 3. The NDVI Map of Jakarta Province in 2018 can be seen in Figure 4. The NDVI Map of Jakarta Province in 2019 is shown in Figure 5. The NDVI Map of Jakarta Province in 2020 is shown in Figure 6. The NDVI Map of Jakarta Province in 2021.

4. Furthermore, from these maps, each area of land with low, medium, and high green values are measured using the Reclassify function: spatial analyst tool in ArcGIS software by calculating the number of pixels for each greenery value and converting it to an area in km$^2$ units [43] where each pixel has a dimension of 10 × 10 m which corresponds to Sentinel-2 resolution with RGB 10 m [45,46].

5. The results of the conversion of the greenness value (NDVI Value) to the area with the km$^2$ unit, from 2017 to 2021 are then entered into the data matrix table which will be processed using the Entropy Method with the DPSIR Framework [11,31] together with secondary data that the researchers obtained, as shown in Table 1. Table of Secondary Data and Vegetation Index Data for Processing Using the Entropy Method in the DPSIR Framework.

The following is the result of processing satellite image data from Sentinel2-A using the NDVI method:

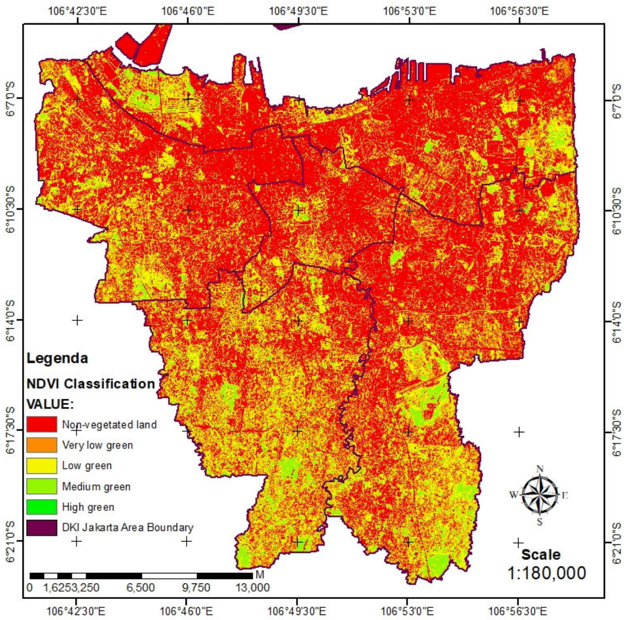


**Figure 2.** NDVI Map of Jakarta Province in 2017. (Source: Researcher Processed with ArcGIS Desktop 10.8).

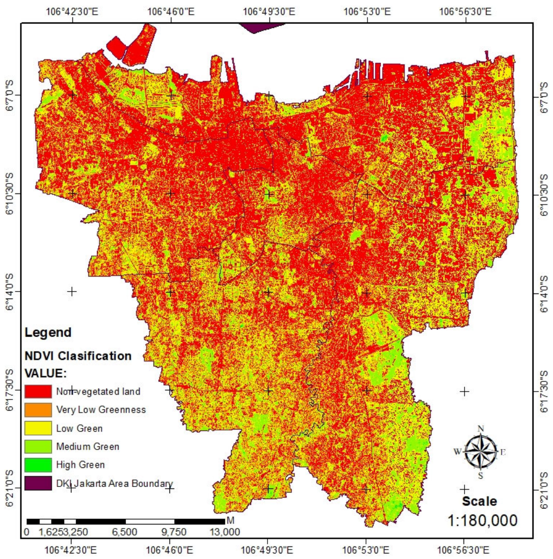


**Figure 3.** NDVI Map of Jakarta Province in 2018. (Source: Researcher Processed with ArcGIS Desktop 0.8).

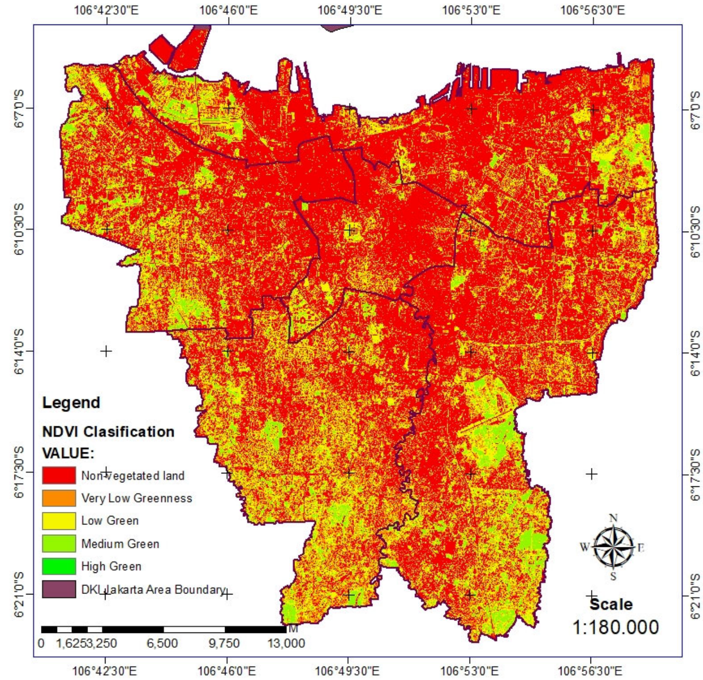


**Figure 4.** NDVI Map of Jakarta Province in 2019. (Source: Researcher Processed with ArcGIS Desktop 10.8).

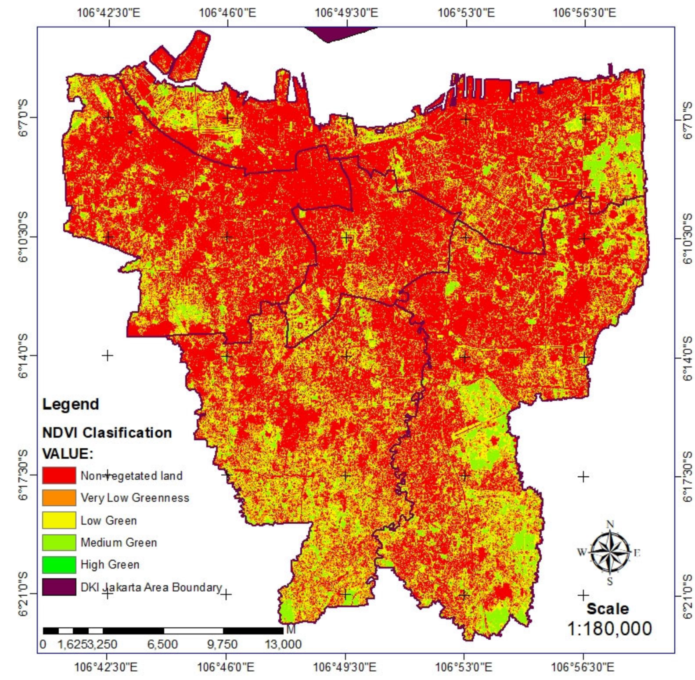


**Figure 5.** NDVI Map of Jakarta Province in 2020. (Source: Researcher Processed with ArcGIS Desktop 10.8).

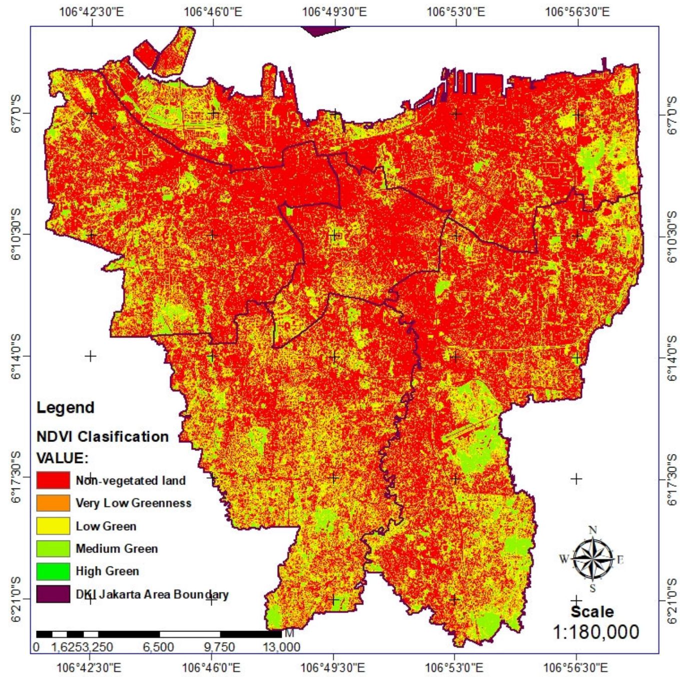


**Figure 6.** NDVI Map of Jakarta Province in 2021. (Source: Researcher Processed with ArcGIS Desktop 10.8).

## 3. Results

### *3.1. Ecological Indicator and NDVI Analysis with DPSIR Framework-Entropy Method*

From Table 1. Secondary Data and Vegetation Index Data to be processed using the Entropy Method in the DPSIR Framework, the researchers processed the data using the Entropy Method, suitable for measuring randomness and disorder in this universe by evaluating the weights of the existing data for Multiple-Criteria Decision-Making (MCDM) [47] problems. The Entropy Method is one of the Objective Weighting Methods [20] where the decision maker in this case the researcher does not have a role or ability in determining the importance of the criteria or at the extreme, the researchers does not know which criterion is the most important.

First, the researchers calculated the initial framework of the DPSIR, namely the Driver and with the same steps carried out for Pressure, State, Impact and Response.

The first step is to normalize the arrangement of the decision matrix (performance index) to obtain the results of the P*ij* project.

$$\mathrm{P}ij = Xij/\sum_{i=1}^{m} Xij \tag{3}$$

The second step is to determine the entropy size of the project P*ij* utilizing the equation below:

$$\mathrm{E}j = -\mathrm{k}\sum_{i=1}^{m}\mathrm{P}ij\,\mathrm{Ln}\,\mathrm{P}ij,\ \text{where}\ \mathrm{k} = 1/\mathrm{Ln(m)} \tag{4}$$

The third step is to determine the objective weight based on the concept of entropy.

$$\mathrm{Wj} = (1-\mathrm{E}j)/\sum_{j=1}^{n}(1-\mathrm{E}j) \tag{5}$$

where E*ij*: Entropy weight function value; d*ij* = 1 − E*ij*: degree of diversity; Wj: weight objective for each criterion.

The results of the calculation of each Driver, Pressure, State, Impact and Response attribute with the Entropy Method are shown in a table sequentially in Table 2. Driver —Objective Weight Results; Table 3. Pressure—Objective Weight Results; Table 4. State —Objective Weight Results; Table 5. Impact—Objective Weight Results; and Table 6. Response —Objective Weight Results.

From the results of the calculation of each attribute of the Driver, Pressure, State, Impact and Response variables using the Entropy Method, the following conclusions can be explained as follows:

**Table 2.** Driver—Objective Weight Results.

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Wj | 0.02% | 0.87% | 0.01% | 0.38% | 5.45% | 47.82% | 45.38% | 0.00% | 0.00% | 0.07% | 0.00% |

(Source: Secondary & NDVI Remote Sensing Data Output by researchers using the Entropy Method, 2022).

**Table 3.** Pressure—Objective Weight Results.

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 | P12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wj | 0.24% | 1.03% | 0.15% | 0.11% | 36.78% | 49.02% | 5.30% | 0.00% | 0.74% | 0.00% | 0.00% | 6.62% |

(Source: Secondary & NDVI Remote Sensing Data Output by researchers using the Entropy Method, 2022).

**Table 4.** State—Objective Weight Results.

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 |
|---|---|---|---|---|---|---|---|---|
| Wj | 0.15% | 0.15% | 0.00% | 22.30% | 6.36% | 0.71% | 1.56% | 0.00% |
| | **S9** | **S10** | **S11** | **S12** | **S13** | **S14** | **S15** | **S16** |
| Wj | 0.00% | 8.73% | 30.39% | 0.07% | 0.10% | 27.67% | 0.00% | 1.81% |

(Source: Secondary & NDVI Remote Sensing Data Output by researchers using the Entropy Method, 2022).

**Table 5.** Impact—Objective Weight Results.

| | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 |
|---|---|---|---|---|---|---|---|---|---|
| Wj | 23.94% | 1.55% | 35.94% | 9.67% | 0.38% | 0.00% | 21.89% | 0.00% | 6.63% |

(Source: Secondary & NDVI Remote Sensing Data Output by researchers using the Entropy Method, 2022).

**Table 6.** Response—Objective Weight Results.

| | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Wj | 2.36% | 7.70% | 0.00% | 0.00% | 4.53% | 0.00% | 0.11% | 4.40% | 0.00% | 80.90% |

(Source: Secondary & NDVI Remote Sensing Data Output by researchers using the Entropy Method, 2022).

From Table 2. Driver—Objective Weight Results, the D6 indicator, namely the growth rate of GRDP in Jakarta and the D7 indicator, namely the industrial growth rate, is the main driver indicator that affects changes in the ecological environment in the Jakarta province, with the respective objective weight values being 47.82% and 45.38%. Followed by the following three major indicators below, namely D5, Gross Regional Domestic Product, D2, the rate of population growth, and D4, income per capita of the population, with the respective objective weight values of 5.45%, 0.87% and 0.38% which are quite influential as drivers of the ecological environment in the Jakarta province.

Meanwhile, from Table 3. Pressure—Objective Weight Results, indicators P6, the amount of water consumption and P5, water consumption per capita, are the main indicators that become a Pressure that affects changes in the ecological environment in Jakarta province, with each objective weight value sequentially 49.02% and 36.78%. This is followed by indicators P12, the number of electricity customers, P7, the annual amount of wastewater ($m^3$/year) and P2, the number of Clean Water Local State-Owned Company customers, with the respective objective weight values being 6.62%, 5.30% and 1.03%, respectively. This is quite influential as an ecological environmental pressure in Jakarta province.

Furthermore, from Table 4. State—Objective Weight Results, the S11 indicator, wind speed, the S14 indicator, rainfall, and the S4 indicator, the loss of water supply, are the main indicators of the current state affecting the ecological environment in the Jakarta province, with the objective weight values, respectively, being 30.39%, 27.67% and 22.30%. This is followed by S10, the annual average concentration of ISPU (Air Pollutant Standard Index), and S5, water consumption of the population per capita, with the objective weight values, respectively, being 8.73% and 6.36%, which are sufficient to be the main indicators affecting the ecological environment in Jakarta province. This complements the shortcomings of previous research from Liu et al. (2020) [15] in that wind speed and rainfall are also ecological indicators that affect the current state of cities. In addition to the general loss of water supply, especially in the Wuhan Metropolitan Area and the DKI Jakarta metropolitan city, the two indicators are wind speed and rainfall which have proven to influence the metropolitan city of Jakarta because these two indicators were not studied in Liu's previous research in the Wuhan Metropolitan Area.

The impact of all the above indicator conditions can be seen in Table 5. Impact —Objective Weight Results; the main indicators are I3, industrial water consumption, I1, industrial water consumption per capita and I7, air quality level, with an objective weight value of each respectively, 35.94%, 23.94% and 21.89%. This is followed by I4, household water consumption and I9, annual electricity consumption, with the objective weight values, respectively, being 9.67% and 6.63%, which are quite influential as the Impact of the ecological environment in Jakarta province.

Finally, Table 6. Response Objective Weights Results shows which of the main indicators respond to the previous indicators. An increase can be seen in the R10 indicator, namely the annual fund for the construction of urban community facilities—PSO (Public Service Obligation). This is a very influential indicator for improving the condition of the ecological environment triggered by previous indicators that became Driver, Pressure, State, and Impact, with an objective weight value of 80.90%. This is much more influential in the Metropolitan City of Jakarta than in the Region Wuhan Metropolitan when compared to previous research conducted by Liu (2020) [15], which only has a weight value of 6.46%. Indicators that need to be improved are the indicator R2, namely the production capacity of water supply, indicator R5 is the volume of treated wastewater, indicator R8 is the domestic waste collected and transported and indicator R1 is the level of water use, each with an objective weight value of 7.70%, 4.53%, 4.40% and 2.36%.

### 3.2. Hypothesis Testing with Partial Least Square Analysis

The next stage is Hypothesis Testing. To test this hypothesis, the researcher did not test the validity and reliability of the secondary data that was processed using the Entropy Method above. Rather, the researcher directly tested the hypothesis using Partial Least Square-Structural Equation Modeling (PLS-SEM) [48] analysis technique to test the structural model using SmartPLS software version 3.2.9 with secondary annual data used as monthly data with the same amount to obtain the minimum data that can be processed by SmartPLS [49].

In this study to find answers to the first and second objectives, researchers have five Latent Variables namely: Driver, Pressure, State, Impact and Response. The Driver variable has the following indicators:

- D1 Population
- D2 Population growth rate
- D3 Level of urbanization
- D4 Population income per capita
- D5 Gross Regional Domestic Product
- D6 Jakarta's GDP growth rate
- D7 Industry growth rate
- D8 Adequate drinking water sources
- D9 Drinking Water Raw Water
- D10 Clean and Drinking Water Production
- D11 Land area of Jakarta province = $km^2$

The Pressure variable has the following indicators:

- P1 Population density per $km^2$
- P2 Number of clean and drinking water customers
- P3 Number of Gas customers
- P4 Gas Usage Ratio
- P5 Water consumption per capita
- P6 Total water consumption
- P7 Annual amount of wastewater ($m^3$/year)
- P8 Number of Industries
- P9 Road surface length
- P10 Green open area
- P11 Quantity of Gas Sold
- P12 Number of electricity customers

State variables have the following indicators:

- S1 Average total water resources
- S2 Total Surface Water Supply
- S3 Total Groundwater Supply
- S4 Loss of water supply
- S5 Water consumption of the population per capita
- S6 Residential waste discharge
- S7 Industrial waste
- S8 Waste is dumped into the river
- S9 Green open space ratio
- S10 Annual average concentration of Air Pollutant Standard Index
- S11 Wind speed
- S12 Temperature
- S13 Humidity
- S14 Rainfall ($mm^2$)
- S15 Soil pH
- S16 Spatiotemporal NDVI (Vegetation Index)

The Impact variable has the following indicators:

- I1 Industrial water consumption per capita
- I2 Number of Industrial Water Customers
- I3 Industrial water consumption
- I4 Household water consumption
- I5 Quantity of water supply
- I6 Green coverage area
- I7 Air quality level
- I8 amount of household gas
- I9 Annual electricity consumption (Wh)

The Response variable has the following indicators:

- R1 Water usage rate
- R2 Production capacity of water supply
- R3 Water supply pipe
- R4 Wastewater treatment rate
- R5 Volume of treated wastewater
- R6 Green coverage ratio
- R7 Gas coverage ratio
- R8 Domestic waste collected and transported (tons/day)
- R9 Number of latrines (goose neck)
- R10 Annual fund construction of municipal community facilities-PSO

Then the initial structural model of the construct variable is obtained as shown in Figure 7.

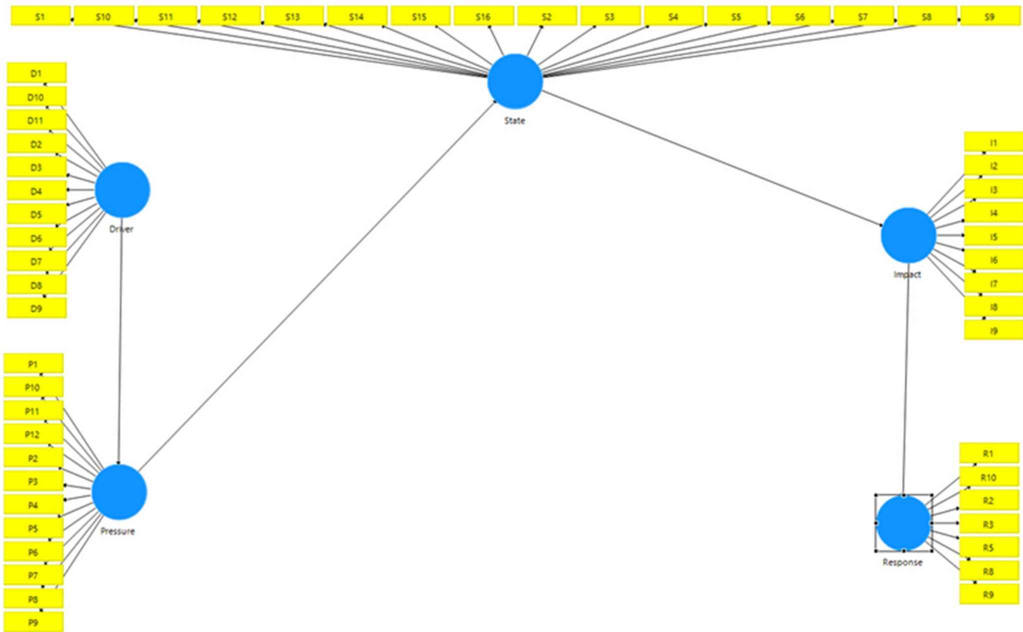


**Figure 7.** Figure of the Initial Structural Model of Secondary Data. (Source: Data Output by researchers with SmartPLS, 2022).

The researcher eliminates variable indicators that have a zero-variance value so that the final model is as follows in Figure 8.

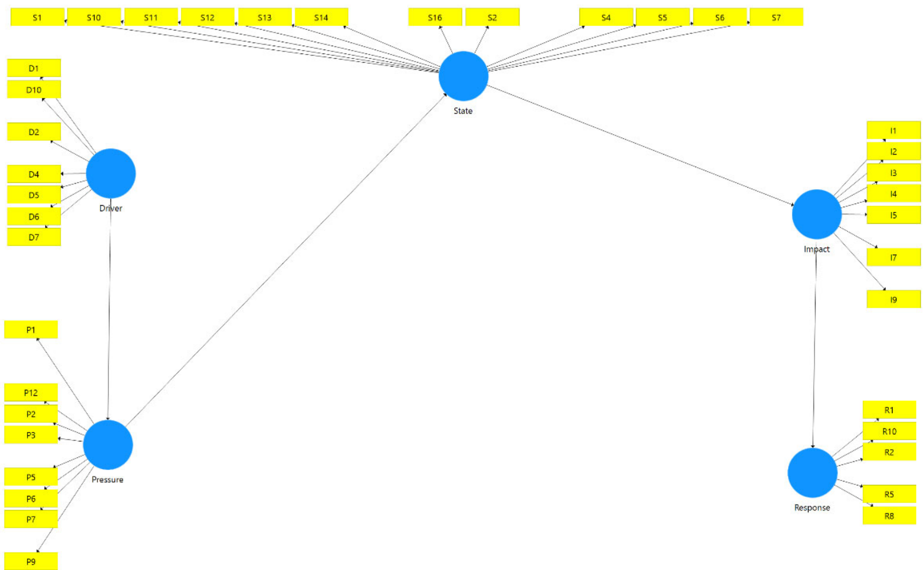


**Figure 8.** Figure of the Final Structural Model of Secondary Data. (Source: Data Output by researchers with SmartPLS, 2022).

The researchers conducted a Hypothesis Test by Resampling Bootstrapping [50] with SmartPLS Software with a number of subsamples = 5000 to overcome the insufficient amount of secondary data. The results showed that the relationship between the latent variable Driver to Pressure, Pressure to State, State to Impact and Impact to Response had a positive effect (strong construct variable) and is significant because the $p$ value was smaller than 0.05.

Based on the Path Coefficient Final Model Test in Table 7, it can be concluded that:

**Table 7.** Path Coefficient Test Results for Secondary Data.

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistic (\|O/STDEV\|) | *p* Values |
|---|---|---|---|---|---|
| Driver -> Pressure | 0.964 | 0.964 | 0.006 | 171.872 | 0.000 |
| Impact -> Response | 0.877 | 0.878 | 0.023 | 38.483 | 0.000 |
| Pressure -> State | 0.986 | 0.985 | 0.003 | 306.549 | 0.000 |
| State -> Impact | 0.919 | 0.919 | 0.012 | 78.325 | 0.000 |

(Source: Data Output by researchers with SmartPLS, 2022).

The *p* value is 0.000 or less than 0.05, indicating that the Driver variable significantly and positively influences the Pressure variable. The positive direction of the association is indicated by the Original Sample (Path Coefficient) value of 0.964. The regression equation for this Driver variable is D = 0.964P.

Since the *p* value is 0.000 or less than 0.05, the Impact variable has a positive and significant impact on the Response variable. The direction of the positive association is indicated by the Original Sample (Path Coefficient) value of 0.877. The regression equation for this Impact variable is I = 0.877R.

Since the *p* value is 0.000 or less than 0.05, the Pressure variable has a positive and significant impact on the State variable. The positive direction of the association is indicated by the Original Sample (Path Coefficient) value of 0.986. The regression equation for this Pressure variable is P = 0.986S.

The *p* value for the State variable is 0.000 or less than 0.05, indicating that it significantly and positively influences the Impact variable. A path coefficient value of 0.919 for the original sample indicates a positive direction for the association. The regression equation for this State variable is S = 0.919I.

Likewise, when viewed from the indirect effect of these latent variables, the indirect effect is also positive and significant as shown in Table 8 below.

**Table 8.** Outer Loading Results (*p*-Values) of Secondary Data After Bootstrapping—Variables.

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistic (\|O/STDEV\|) | *p* Values |
|---|---|---|---|---|---|
| Pressure -> State -> Impact | 0.905 | 0.905 | 0.013 | 69.304 | 0.000 |
| Driver -> Pressure -> State -> Impact | 0.873 | 0.873 | 0.014 | 63.857 | 0.000 |
| State -> Impact -> Response | 0.806 | 0.807 | 0.025 | 32.395 | 0.000 |
| Pressure -> State -> Impact -> Response | 0.794 | 0.795 | 0.026 | 30.004 | 0.000 |
| Driver -> Pressure -> State -> Impact -> Response | 0.766 | 0.766 | 0.028 | 27.725 | 0.000 |
| Driver -> Pressure -> State | 0.950 | 0.949 | 0.007 | 128.006 | 0.000 |

(Source: Data Output by researchers with SmartPLS, 2022).

Meanwhile, from Table 9. Outer Loading Results (*p*-Values) of Secondary Data after Bootstrapping, the results show that Indicators D2, D5, S10, S13 and S14 (there are special notes) are indicators that are not significantly related to the latent variable due to the *p* value being greater than 0.05.

**Table 9.** Outer Loading Results (*p*-Values) of Secondary Data After Bootstrapping—Indicators.

| | Original Sample(O) | Sample Mean(M) | Standard Deviation(STDEV) | T Statistic(∣O/STDEV∣) | *p* Values |
|---|---|---|---|---|---|
| **D1 <- Driver** | 0.900 | 0.901 | 0.019 | 47.884 | 0.000 |
| **D10 <- Driver** | 0.934 | 0.933 | 0.013 | 70.387 | 0.000 |
| **D2 <- Driver** | −0.250 | −0.249 | 0.132 | 1.891 | 0.059 |
| **D4 <- Driver** | 0.867 | 0.863 | 0.035 | 24.807 | 0.000 |
| **D5 <- Driver** | 0.085 | 0.085 | 0.149 | 0.569 | 0.570 |
| **D6 <- Driver** | −0.744 | −0.740 | 0.045 | 16.533 | 0.000 |
| **D7 <- Driver** | −0.630 | −0.620 | 0.079 | 8.002 | 0.000 |
| **I1 <- Impact** | 0.907 | 0.908 | 0.008 | 110.054 | 0.000 |
| **I2 <- Impact** | 0.956 | 0.956 | 0.008 | 123.512 | 0.000 |
| **I3 <- Impact** | 0.932 | 0.933 | 0.006 | 146.602 | 0.000 |
| **I4 <- Impact** | 0.951 | 0.952 | 0.004 | 229.069 | 0.000 |
| **I5 <- Impact** | 0.938 | 0.937 | 0.012 | 81.369 | 0.000 |
| **I7 <- Impact** | −0.420 | −0.415 | 0.092 | 4.540 | 0.000 |
| **I9 <- Impact** | −0.606 | −0.597 | 0.079 | 7.653 | 0.000 |
| **P1 <- Pressure** | 0.974 | 0.974 | 0.005 | 196.298 | 0.000 |
| **P12 <- Pressure** | 0.987 | 0.988 | 0.002 | 417.012 | 0.000 |
| **P2 <- Pressure** | 0.987 | 0.988 | 0.001 | 816.376 | 0.000 |
| **P3 <- Pressure** | 0.739 | 0.733 | 0.055 | 13.463 | 0.000 |
| **P5 <- Pressure** | 0.851 | 0.852 | 0.024 | 35.430 | 0.000 |
| **P6 <- Pressure** | 0.880 | 0.881 | 0.019 | 47.093 | 0.000 |
| **P7 <- Pressure** | 0.985 | 0.985 | 0.001 | 784.352 | 0.000 |
| **P9 <- Pressure** | 0.739 | 0.733 | 0.055 | 13.463 | 0.000 |
| **R1 <- Response** | 0.885 | 0.882 | 0.028 | 31.084 | 0.000 |
| **R10 <- Response** | 0.977 | 0.976 | 0.005 | 184.357 | 0.000 |
| **R2 <- Response** | 0.572 | 0.572 | 0.077 | 7.404 | 0.000 |
| **R5 <- Response** | 0.877 | 0.876 | 0.021 | 41.888 | 0.000 |
| **R8 <- Response** | 0.959 | 0.959 | 0.006 | 156.418 | 0.000 |
| **S1 <- State** | 0.916 | 0.915 | 0.015 | 61.996 | 0.000 |
| **S10 <- State** | −0.190 | −0.188 | 0.124 | 1.527 | 0.127 |
| **S11 <- State** | −0.340 | −0.343 | 0.084 | 4.057 | 0.000 |
| **S12 <- State** | 0.701 | 0.698 | 0.061 | 11.559 | 0.000 |
| **S13 <- State** | −0.129 | −0.116 | 0.147 | 0.875 | 0.382 |
| **S14 <- State** | −0.274 | −0.275 | 0.163 | 1.679 | 0.093 |
| **S16 <- State** | −0.392 | −0.395 | 0.053 | 7.438 | 0.000 |
| **S2 <- State** | 0.916 | 0.915 | 0.015 | 61.996 | 0.000 |
| **S4 <- State** | −0.820 | −0.819 | 0.045 | 18.397 | 0.000 |
| **S5 <- State** | 0.874 | 0.874 | 0.032 | 26.933 | 0.000 |
| **S6 <- State** | 0.992 | 0.991 | 0.005 | 204.454 | 0.000 |
| **S7 <- State** | 0.992 | 0.991 | 0.005 | 204.464 | 0.000 |

(Source: Data Output by researchers with SmartPLS, 2022).

Based on the results of Outer Loading Secondary Data after Bootstrapping or random duplication, the assumption of normality will not be a problem for PLS. In Table 9, it can be concluded that:

Indicators D1 (Number of Population), D10 (Clean and Drinking Water Production), and D4 (Income of population per capita) show a positive and significant relationship towards the latent variable Driver because the $p$ value is 0.000 or less than 0.05, with each Outer Loading being 0.900, 0.934, and 0.867, respectively, while D6 (GDP growth rate of Jakarta) and D7 (Industrial growth rate) indicate a negative and significant relationship towards the latent variable Driver because the $p$ value is 0.000 or more, smaller than 0.05, with the respective Outer Loading values being −0.744 and −0.630, respectively. Especially for the D2 (Population growth rate) indicator, the researchers note that the indicator has a $p$ value almost less than 0.05, which is 0.059, so researchers' inputs also affect the latent variable Driver, with an Outer Loading value of −0.250. The regression equation for this Driver variable is D = 0.900D1 + 0.934D10 + 0.867D4 – 0.744D6 – 0.630D7 – 0.250D2.

Indicators I1 (industrial water consumption per capita), I2 (number of industrial water customers), I3 (industrial water consumption), I4 (household water consumption), and I5 (quantity of water supply), indicate a positive and significant relationship impact on the latent variable Impact because the $p$ value is 0.000 or less than 0.05, with the respective Outer Loading values being 0.907, 0.956, 0.932, 0.951 and 0.938. I7 (Air quality level), and I9 (Consumption annual electricity) indicates the direction of a negative and significant relationship to the latent variable Impact because the $p$ value is 0.000 or less than 0.05, with the respective Outer Loading values being −0.420 and −0.606, respectively. The regression equation for this Impact variable is as follows:

$$I = 0.907I1 + 0.956I2 + 0.932I3 + 0.951I4 + 0.938I5 - 0.420I7 - 0.606I9.$$

Indicators P1 (Population density per km$^2$), P12 (Number of electricity customers), P2 (Number of clean and drinking water customers), P3 (Number of Gas customers), P5 (Water consumption per capita), P6 (Total water consumption), P7 (Total annual wastewater) and P9 (road surface length) indicate the direction of a positive and significant relationship to the latent variable Pressure because the $p$ value is 0.000 or less than 0.05, with each Outer Loading value sequentially being 0.974, 0.987, 0.987, 0.739, 0.851, 0.880, 0.985 and 0.739. The regression equation for the Pressure variable is as follows:

$$P = 0.974P1 + 0.987P12 + 0.987P2 + 0.739P3 + 0.851P5 + 0.880P6 + 0.985P7 + 0.739P9.$$

Indicators R1 (rate of water use), R10 (annual funds for the construction of urban community facilities), R2 (production capacity of water supply), R5 (volume of treated wastewater), and R8 (domestic waste collected and transported) indicate the direction of the relationship which is positive and significant for the latent variable Response because the $p$ value is 0.000 or less than 0.05, with the respective Outer Loading values being 0.885, 0.977, 0.572, 0.877, and 0.959. The regression equation for this Response variable is as follows:

$$R = 0.885R1 + 0.977R10 + 0.572R2 + 0.877R5 + 0.959R8.$$

Indicators S1 (Average total water resources), S12 (Temperature), S2 (Amount of Surface Water Supply), S5 (Water consumption per capita), S6 (Housing waste discharge) and S7 (Industrial waste) show the direction of a positive and significant relationship to the latent variable State, because the $p$ value is 0.000 or less than 0.05, with the respective Outer Loading values being 0.916, 0.701, 0.916, 0.874, 0.992 and 0.992, while S11 (speed wind), S16 (Spatiotemporal NDVI (Vegetation Index)), and S4 (Loss of water supply), indicate the direction of the negative and significant relationship to the latent variable State because the $p$ value is 0.000 or less than 0.05, with each value being, respectively, Outer Loading is −0.340, −0.392 and −0.820. Specifically, for the S14 (Rainfall) indicator, the researchers note that the indicator almost has a $p$ value of less than 0.05, which is 0.091, so the researcher's input also affects the latent State variable, with an Outer Loading value of −0.274. The regression equation for this State variable is:

$$S = 0.916S1 + 0.701S12 + 0.916S2 + 0.874S5 + 0.992S6 + 0.992S7 - 0.340S11 - 0.392S16 - 0.820S4 - 0.274S14.$$

From the hypothesis test above, it can be concluded that:

According to secondary data obtained by researchers, only three ecological indicators, namely Wind Speed, Temperature, and Rainfall, are very influential in Climate Change with the DPSIR Framework to assess the ecological conditions of the urban environment, especially Jakarta Smart City. Likewise, land change data in a spatial (spatiotemporal) time series through the Vegetation Index is very influential in Climate Change with the DPSIR Framework for assessing the ecological conditions of the urban environment.

### *3.3. Comprehensive Influential Indicators and Strategies for Addressing Climate Change*

From the results of processing ecological data collected directly, and data from the remote sensing method from the Sentinel-2 Satellite with the NDVI formula with the DPSIR framework that is calculated by the Entropy objective weight method [51] from C.E Shannon (1948) and the Partial Least Square Structural Equation Modeling (PLS-SEM) [52] method with SmartPLS software, the researchers can summarize in Table 10 which indicators affect the latent variables.

**Table 10.** Summary of Indicators with Significant Influence Based on Secondary Data and Remote Sensing.

| Variable | Significantly Influential Indicators | Method | Source |
|---|---|---|---|
| **Driver (D)** | D6—Jakarta's GDP growth rate | Entropy + PLS | [6,11,15,25,28] |
| | D7—Industry growth rate | Entropy + PLS | [6,11,15,25,28] |
| | D4—Population income per capita | Entropy + PLS | [6,15,28] |
| | D2—Population growth rate | Entropy + PLS | [6,15,28] |
| | D5—Gross Regional Domestic Product | Entropy | [6,15,28] |
| | D1—Total population | PLS | [6,15,28] |
| | D10—Clean and Drinking Water Production | PLS | [6,15,28] |
| **Pressure (P)** | P6—amount of water consumption | Entropy + PLS | [6,15,28] |
| | P5—water consumption per capita | Entropy + PLS | [6,15,28] |
| | P12—number of electricity customers | Entropy + PLS | [6,15,28] |
| | P7—annual amount of wastewater ($m^3$/year) | Entropy + PLS | [6,15,28] |
| | P2—Number of clean drinking water customers | Entropy + PLS | [6,15,28] |
| | P1—Population density per $km^2$ | PLS | [6,15,28] |
| | P3—Number of Gas customers | PLS | [6,15,28] |
| | P9—Road surface length | PLS | [6,15,28] |
| **State (S)** | S11—wind velocity | Entropy + PLS | [6,15,28] |
| | S4—loss of water supply | Entropy + PLS | [6,15,28] |
| | S5—water consumption of the population per capita | Entropy + PLS | [6,15,28] |
| | S14—rainfall | Entropy + PLS | [6,15,28] |

**Table 10.** *Cont.*

| Variable | Significantly Influential Indicators | Method | Source |
|---|---|---|---|
| | S10—Air Pollutant Standards Index annual average concentration | Entropy | [6,15,28] |
| | S16—Spatiotemporal NDVI (Vegetation Index) | PLS | [6,15,28,40] |
| | S6—Residential waste discharge | PLS | [6,15,28] |
| | S7—Industrial waste | PLS | [6,15,28] |
| | S1—Average total water resources | PLS | [6,15,28] |
| | S2—Amount of Surface Water Supply | PLS | [6,15,28] |
| | S12—Temperature | PLS | [6,15,28] |
| **Impact (I)** | I3—industrial water consumption | Entropy + PLS | [6,15,28] |
| | I1—industrial water consumption per capita | Entropy + PLS | [6,15,28] |
| | I7—air quality level | Entropy + PLS | [6,15,28] |
| | I4—household water consumption | Entropy + PLS | [6,15,28] |
| | I9—annual electricity consumption | Entropy + PLS | [6,15,28] |
| | I2—Number of Industrial Water Customers | PLS | [6,15,28] |
| | I5—Water supply quantity | PLS | [6,15,28] |
| **Response (R)** | R10—annual fund for the construction of urban community facilities—PSO | Entropy + PLS | [6,15,28] |
| | R5—volume of treated wastewater | Entropy + PLS | [6,15,28] |
| | R8—domestic waste collected and transported | Entropy + PLS | [6,15,25,28] |
| | R1—water usage rate | Entropy + PLS | [6,11,15,25,28] |
| | R2—water supply production capacity | Entropy | [6,11,15,25,28] |
| | R3—Water supply pipe | PLS | [6,11,15,25,28] |

From Table 10, the results of the Entropy and Partial Least Square SEM methods show almost the same results, and only the results of data processing with SmartPLS have more influential indicators. These influential indicators are more accurate because the relationship between indicators and their latent variables can be displayed as a regression equation. Meanwhile, the results with the Entropy Method can only show the weighted objective weight of each indicator on the latent variable.

The preparation of a Comprehensive Evaluation of Influential Indicators in Jakarta in Table 10 is also used by researchers as a reference to create strategies in dealing with climate change in the metropolitan city of Jakarta as shown in Table 11. Proposed Strategies Framework Managing for Climate Change in The Metropolitan City of Jakarta.

**Table 11.** Proposed Strategic Framework Managing for Climate Change in The Metropolitan City of Jakarta.

| Reponses Category | Responses | Strategy |
|---|---|---|
| **Prevention** | Low production capacity of water supply and high domestic waste collected and transported | 1. Increase the production capacity of drinking water and reduce leakage of clean water pipes. |
| | | 2. Build a more environmentally friendly waste management infrastructure and increase its transportation facilities. |

**Table 11.** *Cont.*

| Reponses Category | Responses | Strategy |
|---|---|---|
| | | 3. Strengthen the growth of other regional industries to reduce urbanization in The Metropolitan City of Jakarta. |
| **Mitigation** | High rate of water uses and low production capacity of water supply | 1. Reducing the risk of lack of clean water by building water sources, infiltration wells and green open areas. |
| | | 2. Building infrastructure such as dams that are multifunctional for not only providing raw water, but also able for irrigation and cultivation. |
| | | 3. Provide education to the community to manage rainwater, irrigate dry topography, and plant trees in the yard. |
| | | 4. Better monitoring of groundwater levels |
| **Restoration** | Increased volume of treated wastewater and high rates of water use | 1. Build an environmentally friendly wastewater treatment facility |
| | | 2. Companies or governments should have incentives to invest in water-saving technologies |
| | | 3. Companies should try to reduce leakage of clean water distribution |
| **Adaptation** | High rate of water uses and low production capacity of water supply | Educate the public to use clean water wisely |

## 4. Discussion

From the results of data processing on ecological indicators that have the impact of climate change, coupled with remote sensing data analyzed with NDVI vegetation density processed with the DPSIR framework with the Entropy Method, it is found that in the last five years in Jakarta province the conditions as follows:

The D6 indicator serves as the principal representative of the elements influencing the development and transformation of resources, particularly when incorporating the environmental theme indicators of ecology, population, economics, meteorology, and energy, namely the growth rate of GRDP in Jakarta and the D7 indicator, namely the growth rate. This happened due to a drastic change in the values of the two variables due to the pandemic in 2020. This change is followed by the following three major indicators, namely: the D5 indicator, Gross Regional Domestic Product, D2, the population growth rate, and D4, the income of the population per capita which also has an effect as an ecological environmental driver variable. This confirms the previous research from Liu et al. (2020) [15] which found that the growth rate of GRDP and the rate of industrial growth are the main drivers of ecological indicators of the urban environment, in general, especially in Wuhan Metropolitan Area and Jakarta metropolitan city.

The pressure variable, on the other hand, describes the demand for natural resources across a range of economic and social development sectors, as well as its effects on population and energy, particularly population status and resource consumption. From the dimensions of this variable, indicator P6 is the amount of water consumption and P5 is the water consumption per capita, both of which are the main indicator that becomes the pressure that affects changes in the ecological environment in the Jakarta province. This is followed by indicator P12, namely the number of electricity customers, P7, the annual amount of wastewater ($m^3$/year) and P2, the number of clean drinking water customers, which are also directly proportional to the P6 variable of water consumption. With the results of this data, the authors conclude that the problem of clean drinking water has become a problem that suppresses the development of Jakarta metropolitan city to be sustainable if a more comprehensive solution is not taken for this water problem. This confirms previous research from Liu et al. (2020) [15] that the amount of water consumption, and water consumption per capita are the main pressure indicators of urban environmental ecology in general, especially in Wuhan Metropolitan Area and Jakarta metropolitan city.

Furthermore, from the dimensions/state variables (States) that describe the degree of resource development and utilization, which can also be used to represent how well the environmental system can support both the production and demands of human existence, the development and exploitation of current resources, the status of the total quality of the ecological environment, environmental resources available, waste treatment capacity, and so on. From this dimension, it is found that indicator S11 (wind speed), variable S14 (rainfall), and variable S4 (loss of water supply), are the main indicators of current conditions affecting the ecological environment in Jakarta province. This is followed by indicator S10, the annual average concentration of Air Pollutant Standard Index, and S5, the water consumption of the population per capita. From this result, the researchers received convincing confirmation that the problem with ecological indicators that previous researchers, namely Liu et al., did not include in their research is indeed the main problem in the current situation in Jakarta province. This is followed by problems with the air environment, which is not good because of the average concentration. Air Pollutant Standard Index's annual trend tends to worsen as seen from the data from 2016 to 2018 which worsened, 2019 and 2020 improved due to the pandemic, but in 2021 it returned to numbers similar to 2018. This complements the shortage of previous research from Liu et al. (2020) [15] that wind speed, and rainfall are ecological indicators that affect the condition of urban areas today besides the loss of water supply, especially in the metropolitan area of Wuhan. The two indicators proven to affect the metropolitan city of Jakarta are wind speed and rainfall because the two indicators did not have time to be examined in previous research on the Wuhan metropolitan area.

The dimension/variable of impact (Impact) refers to the outcome of the ecological environment, which might indicate longer-term changes than the pertinent state indicators, particularly in changes to the amount and quality of ecological environmental resources. From this Impact dimension, the results are obtained with the main indicators being I3, (industrial water consumption), I1 (industrial water consumption per capita), and I7 (air quality level). This is followed by I4, household water consumption and I9, annual electricity consumption. These results also make researchers more confident that the problem of water, air quality and electricity consumption has become a significant problem in the sustainability of the metropolitan city of Jakarta. This confirms previous research from Liu et al. (2020) [15] that industrial water consumption, per capita water consumption and air quality levels are the main impacts of ecological indicators of the urban environment in general, especially in the Wuhan Metropolitan Area and Jakarta metropolitan area.

Finally, the response variable (Response) outlines the management strategies employed to address the vulnerability of environmental systems, such as comprehensive usage of resources, reduction in pollution and treatment, the construction of city public facilities, and others. From this dimension, it is found that the increase in the R10 indicator, the annual fund for the construction of urban community facilities—PSO (Public Service Obligation) is a very influential variable to enhance the state of the ecological environment in Jakarta province compared to Liu's previous research in Wuhan metropolitan area. This is followed by the R2 indicator, the production capacity of water supply, the R5 indicator, the volume of treated wastewater and the R8 indicator, domestic waste collected and transported. These are indicators of response variables that need to be handled comprehensively and holistically so that Jakarta metropolitan city is more prepared to be sustainable.

An Important note from secondary data processing with the DPSIR framework and the Entropy Method conducted by previous researchers, such as Liu et al. (2020) [15], only calculates $P_{ij}$ (Normalization of the Performance Index Matrix) of the Entropy Method for each year from 2014 to 2017, while the researcher counts the objective weight value ($W_j$) for each criterion by considering the degree of diversity from 2016 to 2021.

In this study, the researchers who carried out research in the metropolitan city of Jakarta improved the method carried out by Liu et al. (2020) [15] by including the lack of research conducted by Liu et al. on the elements of ecological indicators and spatio-temporal vegetation index obtained from remote sensing and processed by the DPSIR Method and the Entropy Method. However, the researchers also perfected the framework model by studying the literature from several studies, one of which was carried out by Salehi et al. in Tehran by adopting the DPSIR model from Spangenberg. From the results of community responses, the ways in which we can find solutions and responses to feedback to Drivers, Pressures, States, or Impacts can be found [27]. Responses addressed to Drivers are a form of prevention. If the response controls Pressure on the environment, then the response will be in the form of mitigation. Further, if the response is in the form of protecting the environment, it is a form of restoration. Finally, the response that helps to overcome the impact is a response in the form of adaptation. So, the researchers summarize the results of this study with the proposed Strategic Framework for Managing Climate Change in the metropolitan city of Jakarta which can be adapted in other big cities, as shown in Table 11.

When compared with research conducted by Jinhui Zhao et al., which also uses the DPSIR model framework by combining aspects of the Yellow River Basin which includes important elements such as ecology and socio-economy in a comprehensive manner that is composed of five levels of driving forces, pressures, states, impacts, responses, of which 12 representative elements were then selected [34]. This research in the metropolitan city of Jakarta selected 58 representative elements from the DPSIR framework, so in terms of representation, more elements were studied.

However, if our research is compared with Zhirong Li et al.'s research in Hunan province, we both use the DPSIR method with objective weighting, because in the subjective weighting method, we assign index weights according to the experience of experts in the relevant field, such as: Delphi method, AHP (Analytical Hierarchy Process) and so on. This method is very susceptible to the influence of the field of research and personal cognition, which will affect the results of the weights to some extent [53]. Our research is, relatively speaking, the objective weighting method which avoids the detrimental effects of subjective factors and is more scientifically objective.

Likewise, the research conducted by Shi and Tong evaluates the spatial distribution pattern of ecological city development in 34 cities in China from 2011 to 2016. The data is also taken from statistical data from the China Statistical Yearbook, China City Statistical Yearbook, and others, by also using the entropy method and the TOPSIS method [36]. Our research carried out the same process, extracting a lot of statistical data from the city of Jakarta but also adding research data taken from remote sensing data to see the greenness index of the Jakarta city. Shi and Tong's research compares two types of the same objective method in solving multiple criteria decision-making problems.

Furthermore, in addition to carrying out the above hypothesis, from the results of processing data on ecological indicators that have an impact on climate change and coupled with remote sensing data analyzed for NDVI vegetation density processed with the DPSIR framework using the PLS-SEM method with SmartPLS software, it is obtained as follows:

The main drivers represent the driving factors (Drivers). The main indicators are Indicators D1 (Number of Population), D10 (Clean and Drinking Water Production), and D4 (Income per capita population), indicating the direction of a positive and significant relationship to the latent variable Driver while D6 (GDP growth rate of Jakarta) and D7 (Industrial growth rate) indicate a negative and significant relationship towards the latent variable Driver. This shows that the PLS-SEM Method and the Entropy Method produce the same driver indicators, however, for the PLS-SEM Method, there are additional indicators of Population and Clean Drinking Water Production as the main drivers of resource change, mainly adopting environmental themes indicators of ecology, population, economy, meteorology, and energy.

As for the impact variable, the main indicators are Indicator I1 (industrial water consumption per capita), I2 (number of industrial water customers), I3 (industrial water consumption), I4 (household water consumption), and I5 (quantity water supply), which indicates a positive and significant relationship towards the latent variable Impact. In contrast, I7 (Air quality level), and I9 (Annual electricity consumption) indicates a negative and significant relationship towards the latent variable Impact. This shows that the PLS-SEM Method and the Entropy Method produce the same driver indicators. However, for the PLS-SEM Method, there are additional indicators, namely the Number of Industrial Water Customers and the Quantity of Water Supply as the result of the ecological environment, which can reflect more long-term changes, especially changes in the quantity and quality of ecological environmental resources.

Furthermore, from the pressure variable, the main indicators are Indicators P1 (Population density per km$^2$), P12 (Number of electricity customers), P2 (Number of clean and drinking water customers), P3 (Number of Gas customers), P5 (Water consumption per capita), P6 (Amount of water consumption), P7 (Amount of annual wastewater) and P9 (Length of the road surface) indicate the direction of a positive and significant relationship with the latent variable Pressure. This shows that the PLS-SEM Method and the Entropy Method produce the same driver indicators. However, for the PLS-SEM method there are the additional indicators of population density per km$^2$, number of gas customers, road surface length as environmental resource requirements in various social development sectors, economy, as well as its side effects on population and energy, especially population status and resource consumption.

For the response variable (Response), the main indicators are Indicator R1 (rate of water use), R10 (Annual funds for the construction of urban community facilities), R3 (Water supply pipes), R5 (Volume of treated wastewater), and R8 (Waste domestic collected and transported) indicates a positive and significant direction of the relationship to the latent variable Response as management measures taken for the vulnerability of environmental systems. These include several aspects such as comprehensive resource utilization, pollution handling and prevention, construction of city public facilities, and etc. Both Methods produce the same number of indicators.

The last of the state variables, the main indicators are Indicator S1 (Average total water resources), S12 (Temperature), S2 (Amount of Surface Water Supply), S5 (Water consumption of the population per capita), S6 (Residential waste discharge) and S7 (industrial waste) show a positive and significant relationship towards the latent variable State, while S11 (Wind speed), S16 (Spatiotemporal NDVI (Vegetation Index)), S4 (Loss of water supply), and S14 (Bulk rain) indicates the direction of the negative and significant relationship to the latent variable State. This shows that the PLS-SEM Method and the Entropy Method produce the same driver indicators. However, for the PLS-SEM method, there are additional indicators of Spatiotemporal NDVI (Vegetation Index), Residential waste discharge, Industrial waste, Average total water resources, Total Surface Water Supply, and Temperature as a description of the ability of the environmental system to meet the production and needs of human life as well as the development and utilization of current resources, represented by the degree of development and utilization, the status of the total quality of the ecological environment, available environmental resources, capacity, waste treatment, and others.

The calculation using the entropy method and PLS-SEM method show that the Response indicators (i.e., the R10 indicator, the annual fund for the construction of urban community facilities—PSO or Public Service Obligation) is a very influential indicator to improve the condition of the ecological environment which is triggered by these indicators, Driver, Pressure, State, and Impact previously, with an objective weight value of 80.90%. Even so, big problems still exist in Jakarta, namely the need for clean water for drinking water, which is inadequate, and the management of waste water problems that is felt by the poor residents of Jakarta. This phenomenon should be an input for the Jakarta local government, noting that the use of annual funds for the construction of urban community facilities—PSO is still not well-targeted. Therefore, building clean water sources and their management should be prioritized so that Jakarta will not experience a clean water crisis in the near future.

## 5. Conclusions

The results of the DPSIR model obtained using the Entropy Method in the metropolitan city of Jakarta show that the triggers or *Drivers* related to climate change are population growth rate and industrial growth rate which, although increasing the income of the population per capita and GRDP growth in Jakarta, generate *Pressure*, namely an increase in the amount of water consumption and the annual amount of wastewater which also increases along with the number of electricity and water customers. Based on these triggers and pressures, the state of the environment (*State*) of the city of Jakarta has several environmental changes, such as loss of water supply. It is, therefore, not possible to maintain vegetation in watersheds from upstream to downstream, wind speed and rainfall are affected due to reduced land cover, as well as the concentration of the rising Air Pollutant Standard Index. The *Impact* of these three components is increasing household and industrial water consumption, increasing annual electricity consumption, and deteriorating air quality. Hence, the *Response* to the four interrelated causal variables, one of which is the Jakarta regional government that must increase the annual fund for the construction of urban community facilities (Public Services Obligation), increase the production capacity of water supply, build environmentally friendly wastewater treatment facilities, increase capacity of waste processing infrastructure and transportation fleet, and educate the public to use water wisely. If the response helps to reduce the trigger or *Driver,* then the response is preventive. Further, if the response controls *Pressure* on the environment, then the response will be mitigation. In addition, if the response in maintaining the *State* of the environment, then the response is restoration. Finally, if the response can help to overcome the *Impact*, then in this case it is adaptation. This will be the next strategic framework in dealing with climate change that affects the metropolitan city of Jakarta.

From the results of data processing for the Jakarta province, which is calculated using the Entropy Method and the PLS-SEM Method to validate the hypothesis, it can be concluded that the problems of the Jakarta province in dealing with climate change are the problem of clean and drinking water needs, wastewater and waste management, electricity needs, open area requirements, and air quality as its population grows. These problems require a comprehensive strategic framework such as increasing the production capacity of clean water-drinking water, reducing leakage of clean water pipes, reducing the risk of lack of clean water by building water sources, infiltration wells and green open areas, build infrastructure such as dams that are multifunctional for not only providing raw water, but also irrigation, and aquaculture. The Jakarta local government must try to reduce the leakage of clean water distribution, create a more environmentally friendly waste management, provide education to the community to manage rainwater, irrigate dry topography, and plant plants in their respective yards as well as educate the community to consume clean water and electricity wisely as shown in Table 11.

From the experience and results of the research carried out by researchers so far, it will be useful for further research to understand whether the Partial Least Square-Structural Equation Modeling (PLS-SEM) method is a better and more accurate method when compared to the Entropy Method, especially when analyzing an urban area using the Framework DPSIR with known causality relationship between latent variables. With PLS-SEM measuring the influence of the relationship between variables with five latent variables namely Driver, Pressure, State, Impact and Response and three intervening variables, namely Pressure, State, and Impact can be carried out simultaneously, the number of samples moderate data (relaxed), and does not require a lot of assumptions.

The researchers conclude that there is a novelty from previous research in this study, namely research on the impact of ecological indicators on climate change in Jakarta Province and several inputs and improvements from previous research. As the basis for further research as follows based on data processing carried out by researchers here, there are several ecological indicators, namely Wind Speed, Temperature, Rainfall, Air Pollutant Annual Standard Index, and land change data in a spatial time series (spatiotemporal) through the Vegetation Index, which is very influential in the climate change DPSIR framework for assessing the ecological condition of the urban environment.

**Author Contributions:** Conceptualization, Y.K. and R.F.S.; methodology, Y.K., R.F.S., H.H. and H.S.H.; software, Y.K.; formal analysis, Y.K.; investigation, Y.K.; validation, Y.K.; resources, Y.K.; data curation, Y.K.; writing—original draft preparation, Y.K.; writing—review and editing, Y.K., R.F.S., H.H., H.S.H. and T.H.L.; visualization, Y.K.; supervision, R.F.S., H.H. and H.S.H.; project administration, Y.K and R.F.S.; funding acquisition, R.F.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work is supported by Universitas Indonesia under PUTI Pascasarjana Grant with contract number NKB-340/UN2.RST/HKP.05.00/2022.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Yang, X.; Li, R. Investigating low-carbon city: Empirical study of Shanghai. *Sustainability* **2018**, *10*, 1054. [CrossRef]
2. Baker, J.L. *Climate Change, Disaster Risk, and the Urban Poor: Cities Building Resilience for a Changing World*; World Bank: Washington, DC, USA, 2012.
3. Silva, R.; Martínez, M.; Van Tussenbroek, B.; Guzmán-Rodríguez, L.; Mendoza, E.; López-Portillo, J. A Framework to Manage Coastal Squeeze. *Sustainability* **2020**, *12*, 10610. [CrossRef]
4. Ringenson, T.; Eriksson, E.; Rivera, M.B.; Wangel, J. The limits of the smart sustainable city. In Proceedings of the 2017 Workshop on Computing within Limits, Santa Barbara, CA, USA, 22–24 June 2017; pp. 3–9. [CrossRef]
5. United Nations Department of Economic and Social Affairs. *World Social Report 2020*; United Nations: New York, NY, USA, 2020; ISBN 9789211303926.
6. Badan Pusat Statistik Indonesia Statistik Indonesia 2020. *Stat. Indones.* **2021**, *1101001*, 790. Available online: https://www.bps.go.id/publication/2020/04/29/e9011b3155d45d70823c141f/statistik-indonesia-2020.html (accessed on 8 January 2022).
7. Kementerian Komunikasi dan Informatika. Panduan Pendampingan Penyusunan Masterplan Smart City; Kementerian Komunikasi dan Informatika: 2017. Available online: https://chelonind.co.id/panduan-pendampingan-penyusunan-masterplan-smart-city-aptika/ (accessed on 10 January 2022).
8. Wahyono, F. Manifestasi Program Jakarta Smart City Melalui Sustainable Development Goals Sebagai Ambisi Pembangunan Global. *J. Sustain. Archit.* **2019**, *1*, 1–15.
9. UN Habitat. *Big Data and the 2030 Agenda for Sustainable Development*; Maaroof, A., Ed.; UN Habitat: New York, NY, USA, 2015.
10. Van Bueren, E.; van Bohemen, H.; Itard, L.; Visscher, H. *Sustainable Urban Environments*; Springer: Dordrecht, The Netherlands, 2012; ISBN 978-94-007-1293-5.
11. Qiao, W.; Sun, X.; Jiang, P.; Wang, L. Analysis of the Environmental Sustainability of a Megacity through a Cobenefits Indicator System—The Case of Shanghai. *Sustainability* **2020**, *12*, 5549. [CrossRef]
12. Bibri, S.E.; Krogstie, J. Smart Eco-City Strategies and Solutions for Sustainability: The Cases of Royal Seaport, Stockholm, and Western Harbor, Malmö, Sweden. *Urban Sci.* **2020**, *4*, 11. [CrossRef]
13. Bansal, N.; Shrivastava, V.; Singh, J. Smart Urbanization—Key to Sustainable Cities. In *Real Corp 2015*; CORP–Competence Center of Urban and Regional Planning: Washington, DC, USA, 2015; pp. 551–560. Available online: https://repository.corp.at/21/1/CORP2015_27.pdf (accessed on 18 November 2021).
14. Yachito Engineering Co., Ltd.; Japan International Cooperation Agency. The Simulation Study on Climate Change in Jakarta, Indonesia Final Report. 2012. Available online: http://open_jicareport.jica.go.jp/pdf/12150934.pdf (accessed on 18 November 2021).
15. Liu, Y.; Du, W.; Chen, N.; Wang, X. Construction and Evaluation of the Integrated Perception Ecological Environment Indicator (IPEEI) Based on the DPSIR Framework for Smart Sustainable Cities. *Sustainability* **2020**, *12*, 7112. [CrossRef]
16. Zebardast, L.; Salehi, E.; Afrasiabi, H. Application of DPSIR Framework for Integrated Environmental Assessment of Urban Areas: A Case Study of Tehran. *Int. J. Environ. Res.* **2015**, *9*, 445–456.
17. Heymans, A.; Breadsell, J.; Morrison, G.M.; Byrne, J.J.; Eon, C. Ecological urban planning and design: A systematic literature review. *Sustainability* **2019**, *11*, 3723. [CrossRef]

18. Bibri, S.E. Introduction: The Rise of Sustainability, ICT, and Urbanization and the Materialization of Smart Sustainable Cities. In *Smart Sustainable Cities of the Future*; Springer: Cham, Switzerland, 2018. [CrossRef]
19. Jasrotia, A. Smart Cities & Sustainable Development: A Conceptual Framework. *Asian J. Res. Bus. Econ. Manag.* **2018**, *8*, 42. [CrossRef]
20. Shen, L.; Zhou, J.; Skitmore, M.; Xia, B. Application of a hybrid Entropy-McKinsey Matrix method in evaluating sustainable urbanization: A China case study. *Cities* **2015**, *42*, 186–194. [CrossRef]
21. Abbas, H.; Ghanem, S.; Abahussain, A. Assessing PM2.5 in Bahrain From the DPSIR Framework Perspective. In Proceedings of the 2021 Third International Sustainability and Resilience Conference: Climate Change, Sakheer, Bahrain, 15–16 November 2021.
22. Nezhyva, M.; Mysiuk, V. Sustainable Development Goals: A Business Opportunity. *J. Environ. Sci. Sustain. Dev.* **2022**, *5*, 48–68. [CrossRef]
23. Liang, L.; Wang, Z.; Li, J. The effect of urbanization on environmental pollution in rapidly developing urban agglomerations. *J. Clean. Prod.* **2019**, *237*, 117649. [CrossRef]
24. Toli, A.M.; Murtagh, N. The concept of sustainability in smart city definitions. *Front. Built Environ.* **2020**, *6*, 77. [CrossRef]
25. Carli, R.; Dotoli, M.; Pellegrino, R. Multi-criteria decision-making for sustainable metropolitan cities assessment. *J. Environ. Manage.* **2018**, *226*, 46–61. [CrossRef]
26. Chen, Q.; Dong, H. Sustainable development indicator systems for island cities: The case of zhoushan maritime garden city. *Isl. Stud. J.* **2019**, *14*, 137–156. [CrossRef]
27. Tscherning, K.; Helming, K.; Krippner, B.; Sieber, S.; Paloma, S.G.Y. Does research applying the DPSIR framework support decision making? *Land Use Policy* **2012**, *29*, 102–110. [CrossRef]
28. Jakarta, B.P.D. Provinsi DKI Jakarta Dalam Angka. 2020. Available online: https://jakarta.bps.go.id/publication/2020/04/27/20f5a58abcb80a0ad2a88725/provinsi-dki-jakarta-dalam-angka-2020.html (accessed on 18 November 2021).
29. Yin, R.K. Case Study Research: Design and Methods. 2009. Available online: https://books.google.co.id/books?hl=id&lr=&id=FzawIAdilHkC&oi=fnd&pg=PR1&dq=30.%09Yin,+R.K.+Case+Study+Research:+Design+and+Methods%3B+2009&ots=l_3X4fmR4o&sig=a6sYStjDBFu2yH7dOEWnrcOqSmg&redir_esc=y#v=onepage&q=30.%09Yin%2C%20R.K.%20Case%20Study%20Research%3A%20Design%20and%20Methods%3B%202009&f=false (accessed on 15 January 2022).
30. Sun, C.; Wu, Y.; Zou, W.; Zhao, L.; Liu, W. A Rural Water Poverty Analysis in China Using the DPSIR-PLS Model. *Water Resour. Manag.* **2018**, *32*, 1933–1951. [CrossRef]
31. Lopez-Carreiro, I.; Monzon, A. Evaluating sustainability and innovation of mobility patterns in Spanish cities. Analysis by size and urban typology. *Sustain. Cities Soc.* **2018**, *38*, 684–696. [CrossRef]
32. Kristensen, P. The DPSIR framework. In *Paper Presented at the 27–29 September 2004 Workshop on a Comprehensive / Detailed Assessment of the Vulnerability of Water Resources to Environmental Change in Africa Using River Basin Approach*; UNEP: Nairobi, Kenya, 2004; pp. 1–10. Available online: http://fis.freshwatertools.eu/files/MARS_resources/Info_lib/Kristensen(2004)DPSIR%20Framework.pdf (accessed on 10 January 2022).
33. Salehi, E.; Zebardastb, L. Application of Driving Force-Pressure-State-Impact-Response (DPSIR) Framework for Analyzing the Human habitat in City of Tehran. *Space Ontol. Int. J.* **2015**, *4*, 65–71.
34. Zhao, J.; Xiu, H.; Wang, M.; Zhang, X. Construction of Evaluation Index System of Green Development in the Yellow River Basin Based on DPSIR Model. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *510*, 032033. [CrossRef]
35. Mei, X.U.; Zhu, X.; Jing-Zhi, L.I. Evaluation of Land Ecological Security in Hunan Province Based on DPSIR-TOPSIS Model. *J. Glaciol. Geocryol.* **2012**, *34*, 1265–1272. [CrossRef]
36. Shi, S.X.; Tong, P.S. Evaluation system and spatial distribution pattern of ecological city construction—Based on DPSIR-TOPSIS model. *Appl. Ecol. Environ. Res.* **2019**, *17*, 601–616. [CrossRef]
37. Guedes, A.L.A.; Alvarenga, J.C.; Goulart, M.D.S.S.; Rodriguez, M.V.R.Y.; Soares, C.A.P. Smart Cities: The Main Drivers for Increasing the Intelligence of Cities. *Sustainability* **2018**, *10*, 3121. [CrossRef]
38. Froufe, M.M.; Chinelli, C.K.; Guedes, A.L.A.; Haddad, A.N.; Hammad, A.W.A.; Soares, C.A.P. Smart buildings: Systems and drivers. *Buildings* **2020**, *10*, 153. [CrossRef]
39. Ferenčuhová, S. Not so global climate change? Representations of post-socialist cities in the academic writings on climate change and urban areas. *Eurasian Geogr. Econ.* **2020**, *61*, 686–710. [CrossRef]
40. Rosmasita; Siregar, V.P.; Agus, S.B. Object and Pixel Based Mangrove Classification Using Sentinel-2B Imagery in Liong River, Bengkalis, Riau Province. *J. Ilmun. Teknol. Kelaut. Trop.* **2018**, *10*, 601–615. [CrossRef]
41. Almadani, Y.L.; Adillah, Y.; Maulana Yusuf, M.; Reza Mahbub, M.N.; Fatikhunnada, A. K-means Clustering in Cibarusah Jaya, Bekasi Regency. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *557*, 012085. [CrossRef]
42. Hill, M.J. Vegetation index suites as indicators of vegetation state in grassland and savanna: An analysis with simulated SENTINEL 2 data for a North American transect. *Remote Sens. Environ.* **2013**, *137*, 94–111. [CrossRef]
43. Karan, S.K.; Samadder, S.R.; Maiti, S.K. Assessment of the capability of remote sensing and GIS techniques for monitoring reclamation success in coal mine degraded lands. *J. Environ. Manage.* **2016**, *182*, 272–283. [CrossRef]
44. Pramanik, S.; Areendran, G.; Punia, M.; Sahoo, S. Spatio-temporal pattern of urban eco-environmental quality of Indian megacities using geo-spatial techniques. *Geocarto Int.* **2021**, *37*, 5067–5090. [CrossRef]
45. Hamada, M.A.; Kanat, Y.; Abiche, A.E. Multi-Spectral Image Segmentation Based on the K-means Clustering. *Int. J. Innov. Technol. Explor. Eng.* **2019**, *9*, 1016–1019. [CrossRef]

46. Wu, D.; Johansen, K.; Phinn, S.; Robson, A.; Tu, Y.-H. Inter-comparison of remote sensing platforms for height estimation of mango and avocado tree crowns. *J. Appl. Earth Obs. Geoinf.* **2020**, *89*, 102091. [CrossRef]
47. Stanković, J.J.; Popović, Ž.; Marjanović, I. Assessing Smartness and Urban Development of the European Cities:An Integrated Approach of Entropy and VIKOR. In *Contributions to Management Science*; Springer Science and Business Media Deutschland GmbH, Faculty of Economics, University of Niš: Niš, Serbia, 2021; pp. 69–97. [CrossRef]
48. Yao, T.; Wei, Y.; Zhang, J.; Wang, Y.; Yu, Y.; Huang, W. What influences the urban sewage discharge in China? The effect of diversified factors on the urban sewage discharge in different regions of China. *Environ. Dev. Sustain.* **2021**, *24*, 6099–6135. [CrossRef]
49. Rouli, J. The Influences of Perceived Usefulness and Online Social Network Attribute on the Intentions To Seek and Share Information on Indonesia'S Smart City Digital Platform. *J. Environ. Sci. Sustain. Dev.* **2021**, *4*, 2. [CrossRef]
50. Mousivand, A.; Menenti, M.; Gorte, B.; Verhoef, W. Global sensitivity analysis of the spectral radiance of a soil-vegetation system. *Remote Sens. Environ.* **2014**, *145*, 131–144. [CrossRef]
51. Feng, J.; Gong, Z. Integrated linguistic entropy weight method and multi-objective programming model for supplier selection and order allocation in a circular economy: A case study. *J. Clean. Prod.* **2020**, *277*, 122597. [CrossRef]
52. Wei, Y.; Zhu, X.; Li, Y.; Yao, T.; Tao, Y. Influential factors of national and regional $CO_2$ emission in China based on combined model of DPSIR and PLS-SEM. *J. Clean. Prod.* **2019**, *212*, 698–712. [CrossRef]
53. Li, Z.; Zheng, K.; Zhong, Q. Comprehensive Evaluation and Spatial-Temporal Pattern of Green Development in Hunan Province, China. *Sustainability* **2022**, *14*, 6819. [CrossRef]