Information Fusion for the Development of a Composite Indicator of Criminogenic Factors Using OWA Operators

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Abstract

In this study, the issue of criminogenic factors in the Lizarzaburu parish of Riobamba-Ecuador is addressed, an area marked by a notable increase in crime. Recognizing the complexity of these factors and the need for an integrated approach for their analysis, the use of Ordered Weighted Averaging (OWA) operators for information fusion is proposed, aiming to create a composite indicator that allows for a holistic and accurate measure of criminality in the area. The implementation of OWA operators facilitates effective weighting of these factors, resulting in the creation of a composite indicator that more faithfully reflects the criminogenic dynamics of Lizarzaburu. This study not only provides a valuable tool for diagnosing crime in urban areas but also establishes a methodological foundation for future research and intervention policies in the field of public security.

Keywords: criminogenic factors; OWA operators; composite indicator; information fusion; public security

1. Introduction

The incidence of crime in contemporary times has significantly manifested itself in various nations across the globe, particularly in Latin America. Empirical studies have confirmed the relationship between crime and the economic progress of a country, indicating that in developing nations, crime can act as an obstacle to economic growth, generating instability in economic, political, and social spheres [1].

High crime rates and a sense of insecurity hinder economic development, resulting in a reduction in the quality of life, decreased investment, high security costs, and a negative perception regarding law enforcement and regulations compliance. Crime undermines the rule of law and undermines the perception of security regarding property rights, leading to a decrease in a country's economic growth. In such cases, the economic effects of crime are more noticeable in developing countries due to the population's lack of preparedness to counteract these crimes. [2]

The Ecuadorian city of Riobamba, located in the Andean region of the country, has a particular appeal due to its natural environment and rich cultural history. However, the socioeconomic context, inequality, and crime, like many Ecuadorian cities, are a perennial issue. The crime rate in this region has experienced a worrying increase in recent years. The country is experiencing a wave of violence in which the homicide rate, infanticide, presence of criminal groups, robberies, and violence have increased dramatically, with an alarming rise over a period of four years.

Doi: https://doi.org/10.54216/FPA.120107
Received: January 23, 2023 Revised: April 14, 2023 Accepted: June 18, 2023

Studying crime in this specific area requires a rigorous scientific approach that integrates a variety of research methods and techniques for proper analysis. In such cases, the application of scientific methods is essential to understand the underlying factors contributing to crime and to design effective prevention and control strategies. [3]

The fusion of information from various sources, such as police databases, judicial records, victimization surveys, and academic studies, is essential to obtain a comprehensive and accurate picture of the crime situation in the region. This multidisciplinary and holistic approach allows for addressing the complexity of crime from multiple perspectives and developing interventions tailored to the specific needs and characteristics of the community. [4], [5]

In this sense, the application of aggregation operators [6] represents a promising tool for creating composite crime indicators. A general aggregation operator (A) can be defined as a function that takes a set of n input values $(x_1, x_2, \dots, x_n$ and maps them to a single output value y, i.e.,

$$A: [a, b]^n \to [a, b] \tag{1}$$

where $[a, b]$ is the interval within which the input values and the output value lie. The exact nature of A depends on the specific aggregation method being applied.

These operators allow for the systematic combination of multiple variables, taking into account the uncertainty and variability inherent in the data [7], [8]. The advantage of aggregation operators lies in their ability to model different degrees of relative importance among variables and to capture the heterogeneity and complexity of social phenomena [9]. In this way, their application and utilization for crime are feasible.

The exploration of aggregation operators constitutes a well-established area within decision sciences, with applications ranging from consolidating information for economic growth [10] to prioritizing disease genes based on networks [11]. Nearly all challenges associated with multi-criteria decision-making (MCDM) rely on the use of aggregation operators to consolidate evaluations of alternatives based on multiple criteria. The choice of aggregation operator significantly influences the determination of the best alternatives. Over the past two decades, a wide range of aggregation operators have been introduced in scholarly articles.

Among the operators, the Ordered Weighted Averaging (OWA) operator stands out as one of the most popular, having been applied in a wide variety of contexts [12], [13]. Other operators have emerged as extensions of the OWA, such as the Induced OWA (IOWA) [6], the Generalized OWA (GOWA) [14], the Fuzzy OWA (FOWA) [15], the Generalized Induced OWA, the Intuitionistic Fuzzy OWA (IFOWA), and the Induced Int-Fuzzy OWA (I-IFOWA) operator. Additionally, the Ordered Weighted Geometric (OWG) operator has been proposed in [16].

In this context, it is evident that the application of OWA operators in creating a crime indicator offers a robust and flexible methodology for integrating multiple variables and capturing the complexity of this social phenomenon. Its use can provide a valuable tool for assessing and monitoring the security situation in a specific region, as well as for formulating policies and strategies for crime prevention and control.

The objective of this research focuses on exploring the potential of OWA operators in the design and development of a composite crime indicator that is adaptable to various situations. The fundamental purpose is to leverage the flexibility and capability of OWA operators to integrate multiple variables related to crime, considering their relative importance and the heterogeneity of factors influencing this social phenomenon. The goal is to develop a solid methodological approach that allows capturing the complexity and dynamics of crime, thus offering a more accurate and comprehensive representation of the situation in the Lizarzaburu region. In this sense, the aim is to contribute to the development of innovative analytical approaches that promote a deeper understanding and more effective management of public security in Ecuadorian urban and rural environments.

Doi: https://doi.org/10.54216/FPA.120107
Received: January 23, 2023 Revised: April 14, 2023 Accepted: June 18, 2023

2. OWA operators

The fusion of information involves combining multiple datasets to produce a single consolidated output. Aggregation operators represent a class of mathematical functions used specifically for this purpose. These operators take as inputs n values belonging to a domain D and generate a single value in that same domain.

An OWA is defined as a function $F: \mathbb{R}^n \rightarrow \mathbb{R}$ of dimension n when associated with a vector W of dimension n, where each element w_j of the vector belongs to the interval [0,1], and the sum of all elements of the vector is equal to 1. This definition is expressed mathematically as follows [17]:

$$F(a_1, a_2, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j \quad (2)$$

Where b_j represents the j-th ordered value of the a_j.

OWAs are widely recognized in various applications, being considered one of the most popular in the field of information aggregation. Their versatility is evidenced in numerous applications, spanning a wide spectrum that includes everything from strategic decision-making to MCDM under different conditions of uncertainty. In the context of MCDM, the goal is to identify the best alternative among several options, taking into account multiple criteria.

Formulations of aggregation operators have been developed that extend the functionality of the OWA operator and weighted mean, allowing for the weighting of variables according to their importance and adjusting the information valuation according to the decision maker's attitude. Among these formulations are the Weighted Ordered Weighted Averaging (WOWA) operator and the Ordered Weighted Averaging with Weights in Arithmetic Mean and the OWA (OWAWA) operator. [18]

These operators allow the aggregation of sets of values using two weight vectors. One of these vectors corresponds to the weights in the arithmetic mean, while the other corresponds to the weights in the OWA operator. The OWAWA operator, in addition to merging the OWA and weighted mean operators, offers the possibility of adjusting the emphasis given to each of these operators.

An OWAWA operator is defined as an OWAWA function: $\mathbb{R}^n \rightarrow \mathbb{R}$ of dimension n if associated with a weight vector W, where the sum of the elements of the vector is equal to 1, and each element of the vector belongs to the interval [0,1]. The OWAWA function is mathematically expressed as [18]:

$$OWAWA(a_1, a_2, \ldots, a_n) = \sum_{j=1}^{n} \hat{v}_j b_j \quad (3)$$

Where b_j is the j-th largest value of the a_i, each argument a_i has an associated weight v_i with the sum of the elements of the vector equal to 1, and each element belonging to the interval [0,1]. Additionally, $\hat{v}_j$ is calculated as a linear combination of two weights, one obtained from the OWA operator (w_j) and another from the weighted average (v_j), allowing the emphasis of each weight to be adjusted according to the corresponding value in the dataset, as shown in (3) [19].

Establishing weights for an OWA operator presents a challenge that can be approached through various methods, such as utilizing relative linguistic quantifiers[6] . These quantifiers, which include terms like most, few, many, and all, can be depicted as fuzzy subsets within the unit interval. Of particular interest are the Regular Increasing Monotone (RIM) quantifiers, which are frequently applied in conjunction with OWA operators due to their characteristic properties[16]:

- The quantifier value is 0 when the degree of membership is 0.
- The quantifier value is 1 when the degree of membership is 1.
- The quantifier value is non-decreasing as the degree of membership increases.

Doi: https://doi.org/10.54216/FPA.120107
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For instance, the RIM quantifier labeled "most" can be defined with parameters a = 0.5 and b = 0.7, resulting in a quantifier Q(r) that behaves as follows: it remains at 0 for r < 0.5, then transitions in a linear fashion as r varies between 0.5 and 0.7.

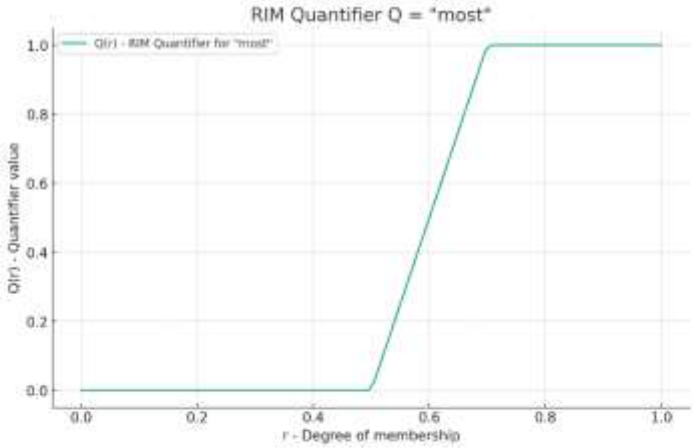

Figure 1: Example of linguistic quantifier Q =“most”

The vector associated with the weighted average can be obtained using the Analytic Hierarchy Process (AHP) method.

$$\hat{v}_j = \beta w_j + (1-\beta)v_j \tag{4}$$

where $\hat{v}_j$ represents the adjusted criteria importance vector, v_j is the original weight of the criteria based on AHP, w_j is the criteria importance vector obtained by another method, and β is a parameter that adjusts the relative importance between w_j and v_j.

3. The Proposed Model

The present research was based on a methodological approach aimed at developing a crime indicator in the city of Riobamba, Ecuador, using ordered weighted averaging (OWA) operators. This approach integrated various scientific techniques and procedures to identify and evaluate the most influential crime factors in the region, as well as to design a composite indicator that accurately and comprehensively reflected the criminal situation.

The research adopted a cross-sectional design, allowing for a snapshot of the crime situation in the region at a specific point in time. A mixed-method approach was used, combining quantitative and qualitative methods to collect and analyze data. This research is framed within an applied research design, aimed at solving practical problems and generating knowledge useful for decision-making. A mixed-method approach was employed, combining qualitative and quantitative methods, as well as participatory techniques involving experts, to integrate different perspectives and maximize the validity and reliability of the results.

The adopted methodology consisted of several interrelated stages (Figure 2). Firstly, a comprehensive review of the literature related to crime in Riobamba and similar cities was conducted. This review aimed to identify the most relevant crime factors and their effects on public safety. Subsequently, the selection of the most appropriate crime factors for the analyzed region was carried out, for which an initial list was developed based on the literature review and consultations with security and criminology experts. This list included elements such as homicide rates, incidence of theft, presence of gangs, and drug trafficking, among others.

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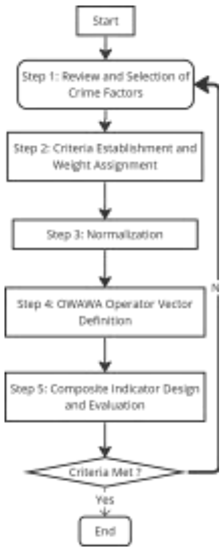

Figure 2: Proposed Model

Subsequently, four evaluation criteria were established to screen among the selected factors, considering the frequency of occurrence (c_1), the severity of the impact (c_2), the feasibility of intervention (c_3), and the cost of implementing preventive measures (c_4). Based on this, a participatory approach involving experts was used to assign weights to the crime factors according to their relative importance, taking into account the previously established evaluation criteria.

The utility vector is presented in sets, where each set $V_j = \{v_{j1}, v_{j2}, \dots, v_{jn}\}$ represents the preferences associated with each criterion c_k of factor R_j. Each value v_{jk} indicates the assessment of the relative importance of the criterion c_k in relation to the factor R_j. This assessment is made on a normalized scale ranging from 0 to 1, where 0 represents the lowest preference and 1 is the highest preference.

The normalization of preference values is carried out considering whether they are of benefit or cost type. For benefit-type criteria, the normalized value, denoted as $\tilde{v}_{jk}$, is calculated using the formula:

$$\tilde{v}_{jk} = \frac{v_{k\,min} - v_{jk}}{v_{k\,min} - v_{k\,max}} \quad (5)$$

For cost-type criteria, the formula used is:

$$\tilde{v}_{jk} = \frac{v_{k\,max} - v_{jk}}{v_{k\,max} - v_{k\,min}} \quad (6)$$

Where $v_{k\,min}$ represents the minimum rating in relation to criterion k, and $v_{k\,max}$ is the maximum rating with respect to the same criterion.

Subsequently, the vectors of the OWAWA operator are defined, where the V vector represents the importance of the criteria and the W vector represents the level of optimism/pessimism and, consequently, the level of risk.

Each value in the V vector defines the importance of the corresponding criterion. To determine the V vector, the AHP method was used, which involves the identification of criteria and sub-criteria, as well as the assignment of weights through pairwise comparisons.

In the subsequent stage, the normalized preference values were combined to obtain a single numerical value using the OWAWA operator. The values were ranked in descending order based on the obtained value. The use of aggregation operators provides flexibility and adaptability to the method. Another strength lies in the ability to directly obtain decision-maker preferences and represent them in weight vectors.

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Received: January 23, 2023 Revised: April 14, 2023 Accepted: June 18, 2023

Based on the results of the relative importance analysis, a composite indicator was designed using the OWAWA operator. This indicator allowed the integration of different crime factors weighted according to their relevance and influence on public safety. Finally, the practical utility of the composite indicator in decision-making and public policy formulation was evaluated through the pilot application of the indicator in collaboration with local authorities and security experts.

4. Results

In the analyzed context, various crime factors are examined to evaluate their inclusion in the composite indicator. To carry out this process, the decision was made to select the evaluation criteria c_1, c_2, c_3, c_4as described earlier. Subsequently, the assessment of each requirement was carried out with the chosen criteria, as illustrated in Table 1.

Table 1: Assessment of the factors

Factors	c_1	c_2	c_3	c_4
Homicide rate	0.9	1	0.8	0.5
Robbery index	0.5	0.8	0.7	0.6
Frequency of sexual assaults	0.3	0.8	0.7	0.7
Incidence of domestic violence	0.4	0.8	0.3	0.7
Vandalism index	0.6	0.6	0.7	0.6
Presence of gangs	0.7	1	0.9	0.8
Drug trafficking	0.8	1	0.9	0.8
Level of police corruption	0.6	0.8	0.6	0.6
Incidence of cybercrimes	0.2	0.4	0.4	0.3

The criterion associated with the cost of implementing preventive measures is classified as a cost-type criterion and is normalized following the procedure described in equation (5). On the other hand, the benefit-type criteria are normalized according to equation (4). The results of this normalization process are presented in Table 2.

Table 2: Data normalization

Factors	c_1	c_2	c_3	c_4
Homicide rate	0.00	0.00	0.17	0.60
Robbery index	0.57	0.33	0.33	0.40
Frequency of sexual assaults	0.86	0.33	0.33	0.20
Incidence of domestic violence	0.71	0.33	1.00	0.20
Vandalism index	0.43	0.67	0.33	0.40
Presence of gangs	0.29	0.00	0.00	0.00

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Drug trafficking	0.14	0.00	0.00	0.00
Level of police corruption	0.43	0.33	0.50	0.40
Incidence of cybercrimes	1.00	1.00	0.83	1.00

By applying the AHP method, the weight structure presented in Table 3 was derived. These weights, resulting from the hierarchical analysis, translate into a weight vector linked to the criteria, represented as V. This process of weight assignment is based on the systematic comparison and evaluation of the criteria, allowing for appropriate weighting that reflects their relative importance in the study context.

Table 3: Data normalization

Criteria	**C1**	**C2**	**C3**	**C4**	**V weight vector**
C1	1	1/5	1/3	1/3	0.08
C2	5	1	1	3	0.40
C3	3	1	1	3	0.36
C4	3	1/3	1/3	1	0.16

The vector W, on the other hand, is defined as W = [0.2 0.35 0.2 0.25]. In this context, greater relevance is assigned to the weighted average, expressed as $\beta = 0.4$. The results obtained from the aggregation process are presented in detail in Table 4. This approach highlights the prioritization of certain criteria over others, reflecting a weighted consideration of information in generating results.

Table 4: Aggregate Operator Results

Factors	**OWAWA**
Homicide rate	0.87
Robbery index	0.58
Frequency of sexual assaults	0.51
Incidence of domestic violence	0.33
Vandalism index	0.48
Presence of gangs	0.77
Drug trafficking	0.79
Level of police corruption	0.55
Incidence of cybercrimes	0.25

The results of the application of the aggregation operator show that the homicide rate, with a value of 0.87, exhibits the highest weighting among all factors considered. This result suggests that the *Homicide Rate* has been identified as the most relevant factor in the studied context, indicating a

Doi: https://doi.org/10.54216/FPA.120107
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significant concern regarding public safety. Additionally, both *Drug Trafficking* and the *Presence of Gangs* obtained high values of 0.79 and 0.77 respectively, suggesting a strong inclination of experts to consider these factors as very predominant in the area's crime.

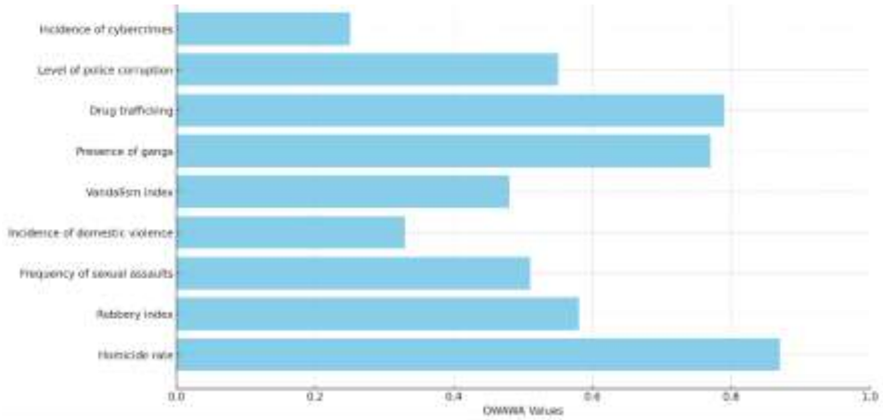

Figure 3: Relative Importance of Crime Factors in Public Safety Assessment

On the other hand, the *Incidence of Cybercrimes* presents the lowest value of 0.25 among all evaluated factors. This could indicate that, although cybercrime incidence is an emerging concern, its impact on overall crime in the region is minor compared to other types of crimes.

In this case, the creation of the composite indicator can include as many factors as desired, depending on the complexity and specificity of the situation studied. The ability to incorporate multiple factors provides a more comprehensive and detailed view of the crime situation in the region, allowing for a more accurate and exhaustive assessment of associated risks and challenges. The inclusion of a wide range of relevant factors, such as the homicide rate, drug trafficking, and gang presence, among others, allows for capturing the complexity and interrelation of various aspects influencing crime. However, it is important to consider that the inclusion of a large number of factors can increase the complexity of the indicator and the difficulty in interpreting the results. Therefore, it is essential to carefully select the most relevant and significant factors and ensure that the resulting indicator is understandable and useful for decision-making and policy formulation.

It is important to note that the results obtained may vary depending on the particular context of each community or situation. The selection of specific factors and the weights assigned to each one can significantly influence the outcome of the crime index. Therefore, it is essential to consider the unique characteristics of each environment when applying this methodological approach. Additionally, it should be noted that this crime index does not exhaust all possible variables that may contribute to the criminal phenomenon. In future research, other additional factors could be considered to enrich the analysis and provide a more comprehensive understanding of the criminal dynamics in the studied community, as well as in other related contexts.

5. Discussion

The use of aggregated operators in the field of crime evaluation has proven to be an effective methodological strategy for synthesizing information from multiple factors. In this study, the application of the weighted OWAWA operator has allowed for the construction of a composite indicator that integrates significant criteria, providing a precise and weighted representation of the criminal dynamics in Lizarzaburu. The relevance of this approach lies in its ability to capture the complexity of crime by considering the relative importance of each factor, thus providing a more comprehensive view of the criminal situation.

Furthermore, the application of these operators in security management and crime prevention has important implications, as it provides decision-makers with an effective tool to identify and prioritize

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intervention areas in different scenarios. In this way, it is possible to design more effective prevention strategies by focusing on the critical factors that influence crime.

Similar to the current study, the research conducted by [20] observed the use of different aggregation tools to create composite indices and evaluate their potential effects on mitigation and adaptation efforts. On the other hand, in [21], they create and apply a composite indicator to map the urban public infrastructure of a Brazilian city. In this context, it is evident that the specific applications of the OWAWA operator and its ease in creating robust composite indicators may vary depending on the context and objectives of each study.

However, there were very few references to the use of aggregated operators in the context of crime analysis and even fewer in the context of creating composite indicators. Nevertheless, the results obtained in this study suggest that the use of aggregated operators, such as OWAWA, can be highly beneficial for integrating multiple factors in a weighted manner and obtaining a comprehensive measure of crime in a particular geographical area.

6. Conclusion

In this study, a composite crime indicator was developed for the Lizarzaburu Parish using ordered weighted averaging (OWA) operators. The methodology employed a combination of quantitative and qualitative techniques, along with the participation of security and criminology experts. Through this approach, the most relevant crime factors in the region were identified and evaluated, leading to the design of a composite indicator that accurately reflected the crime situation. The use of weighted operators allowed for greater flexibility in weighting factors, facilitating model adaptation to the specific needs of the studied community. The obtained crime index provides a useful tool for assessing and monitoring the security situation in the community, as well as informing the formulation of crime prevention policies and strategies. However, it is essential to acknowledge the limitations and consider the possibility of integrating other relevant factors to improve the accuracy and applicability of this approach in the field of study and other related fields.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

References

[1] E. Goulas and A. Zervoyianni, “Economic growth and crime: Is there an asymmetric relationship?,” *Econ. Model.*, vol. 49, pp. 286–295, 2015, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0264999315001157.

[2] I. N. Kathena and J. P. S. Sheefeni, “The relationship between economic growth and crime rates in Namibia,” *Eur. J. Basic Appl. Sci. Vol*, vol. 4, no. 1, pp. 51–62, 2017, [Online]. Available: http://idpublications.org/wp-content/uploads/2016/12/Full-Paper-THE-RELATIONSHIP-BETWEEN-ECONOMIC-GROWTH-AND-CRIME-RATES-IN-NAMIBIA.pdf.

[3] R. Qu, “A Method for Locating Juvenile Criminal Responsibility Procedure Based on Multi-Source Data Fusion,” in *2022 6th Asian Conference on Artificial Intelligence Technology (ACAIT)*, 2022, pp. 1–10, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10137975/.

[4] H. J. Steinhauer and A. Karlsson, “Information fusion,” *Data Sci. Pract.*, pp. 61–78, 2019, [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-97556-6_4.

[5] D. Camacho, A. Panizo, G. Bello, A. Gonzalez, and E. Cambria, “The four dimensions of social network analysis: An overview of research methods, applications, and software tools,” *Inf. Fusion*, vol. 63, pp. 88–120, 2020, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1566253520302906.

[6] R. R. Yager, “Induced aggregation operators,” *Fuzzy sets Syst.*, vol. 137, no. 1, pp. 59–69, 2003, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0165011402004323.

Doi: https://doi.org/10.54216/FPA.120107
Received: January 23, 2023 Revised: April 14, 2023 Accepted: June 18, 2023

[7] B. Talukder, K. W. Hipel, and G. W. vanLoon, “Developing composite indicators for agricultural sustainability assessment: Effect of normalization and aggregation techniques,” *Resources*, vol. 6, no. 4, p. 66, 2017, [Online]. Available: https://www.mdpi.com/2079-9276/6/4/66.
[8] N. Rogge, “Composite indicators as generalized benefit-of-the-doubt weighted averages,” *Eur. J. Oper. Res.*, vol. 267, no. 1, pp. 381–392, 2018, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0377221717310597.
[9] M. Palanikumar, A. Iampan, S. Broumi, and G. Balaji, “Generalization of Neutrosophic interval-valued soft sets with different aggregating operators using multi-criteria group decision-making,” *Int. J. Neutrosophic Sci.*, vol. 22, no. 1, p. 114, 2023, [Online]. Available: https://www.researchgate.net/profile/Dr-M-Palanikumar/publication/374005408_Generalization_of_neutrosophic_interval-valued_soft_sets_with_different_aggregating_operators_using_multi-criteria_group_decision-making/links/65095716d5293c106cc6708c/Generalization-of-neutrosophic-interval-valued-soft-sets-with-different-aggregating-operators-using-multi-criteria-group-decision-making.pdf.
[10] J. M. Merigo, M. Peris, A. Navarro, and C. Rueda, “Aggregation operators in economic growth analysis and entrepreneurial group decision-making,” *Appl. Soft Comput.*, vol. 47, pp. 141–150, 2016, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S1568494616302411.
[11] N. Grewal, S. Singh, and T. Chand, “Effect of aggregation operators on network-based disease gene prioritization: a case study on blood disorders,” *IEEE/ACM Trans. Comput. Biol. Bioinforma.*, vol. 14, no. 6, pp. 1276–1287, 2016, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7539612.
[12] J. C. Alcantud, G. Santos, and M. Akram, “OWA aggregation operators and multi-agent decisions with N-soft sets,” *Expert Syst. Appl.*, vol. 203, p. 117430, 2022, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417422007680.
[13] Z. Xu, “An overview of methods for determining OWA weights,” *Int. J. Intell. Syst.*, vol. 20, no. 8, pp. 843–865, 2005, [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/int.20097.
[14] H. Zhao, Z. Xu, M. Ni, and S. Liu, “Generalized aggregation operators for intuitionistic fuzzy sets,” *Int. J. Intell. Syst.*, vol. 25, no. 1, pp. 1–30, 2010, [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/int.20386.
[15] H. Liao and Z. Xu, “Intuitionistic fuzzy hybrid weighted aggregation operators,” *Int. J. Intell. Syst.*, vol. 29, no. 11, pp. 971–993, 2014, [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/int.21672.
[16] Z. Xu and R. R. Yager, “Some geometric aggregation operators based on intuitionistic fuzzy sets,” *Int. J. Gen. Syst.*, vol. 35, no. 4, pp. 417–433, 2006, [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/03081070600574353.
[17] R. Mesiar, L. Šipeky, P. Gupta, and J. LeSheng, “Aggregation of OWA operators,” *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 1, pp. 284–291, 2017, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7820105/.
[18] W. Hussain, J. M. Merigó, and M. R. Raza, “Predictive intelligence using ANFIS-induced OWAWA for complex stock market prediction,” *Int. J. Intell. Syst.*, vol. 37, no. 8, pp. 4586–4611, 2022, [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/int.22732.
[19] J. M. Merigo, K. J. Engemann, and D. Palacios, “Decision making with Dempster-Shafer belief structure and the OWAWA operator,” *Technol. Econ. Dev. Econ.*, vol. 19, no. sup1, pp. S100–S118, 2013, [Online]. Available: https://www.tandfonline.com/doi/abs/10.3846/20294913.2013.869517.
[20] E. A. Machado and S. Ratick, “Implications of indicator aggregation methods for global change vulnerability reduction efforts,” *Mitig. Adapt. Strateg. Glob. Chang.*, vol. 23, pp. 1109–1141, 2018, [Online]. Available: https://link.springer.com/article/10.1007/s11027-017-9775-7.
[21] E. Fusco, M. Pereira, H. Rabiei-Dastjerdi, F. Vidoli, C. Brunsdon, and P. Iakovlevitch, “Harnessing Spatial Heterogeneity in Composite Indicators through the Ordered Geographically Weighted Averaging (OGWA) Operator,” *Geogr. Anal.*, 2023, [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1111/gean.12384.

Doi: https://doi.org/10.54216/FPA.120107
Received: January 23, 2023 Revised: April 14, 2023 Accepted: June 18, 2023