A Novel Framework to Strengthen Early Warning Systems

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ABSTRACT

The impact of disasters on the population and environment is an important research area. Multiple criteria need to be analyzed while making policy decisions in order to control the effect of a disaster. Researchers have used many variants of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a Multi-Criteria Decision-Making (MCDM) method for prioritizing the alternatives. Additionally, the detrimental effects of disasters have compelled stakeholders to proactively prepare by strengthening crucial key elements of an Early Warning System (EWS) so that timely alerts can be produced. In this paper, a Disaster Information Provider (DIP) framework is proposed, which employs a TOPSIS variant to bolster weak elements of a people-centric EWS. Governments may utilize delivered rankings to strengthen the weak elements of the EWS in an affected area. Extensive experimentation proves the usability of the DIP framework for strengthening EWS.

Keywords-MCDM; TOPSIS; disaster management; EWS

I. INTRODUCTION

Disasters severely impact an area, often beyond its response capacity, leading to environmental impact and considerable loss of human life and property [1]. To contain the spread and considerably reduce the impact of disasters, there is a need for an upgraded Early Warning System (EWS) [2].

A. Background and Motivation

In 2020, use of multi-hazard EWSs successfully protected human life in 23 UN countries with a success rate of 93.63% [2], which proves their relevance and appropriateness. Communities, local organizations, and governments utilize EWSs to assess the risk and warn people in advance so that timely action could be taken [3]. Authors in [4] developed an EWS to mitigate the overall morbidity and mortality rates. Authors in [5] reviewed existing EWS methodologies for real time identification of at-risk patients in hospitals. Authors in [6] advocated the expansion of EWS for better forecasting and anticipatory action. The World Meteorological Organization recently employed Impact Based Forecasting (IBF), which creates warnings highlighting potential implications of a climate related threat in addition to providing weather information [7]. Authors in [8] suggested a low cost EWS to the people residing in nearby wildlife areas to resolve human-wildlife conflicts [8]. Governments all over the world look for different ways to strengthen their respective EWSs. Driven by this objective, we propose a novel method to strengthen people-centric EWS for better disaster preparedness in the future.

B. Contribution

In 2020, Data Knowledge Group (DKG) provided a COVID-19 Regional Safety Assessment Analytical Framework [9]. It ranked 200 affected regions emphasizing on monitoring 6 criteria (quarantine efficiency, government efficiency of risk management, monitoring and detection, health readiness, regional resilience, and emergency preparedness). Such monitoring enables the government to lay out strategic plans for disaster preparedness. Motivated by this, we propose a novel Disaster Information Provider (DIP) framework. The ranking provided by DIP signals the disaster readiness of a region in comparison to other regions. This knowledge can be used by weaker regions (having lower ranking) to prepare against future disasters of a similar nature more effectively. Extensive experimentation was carried out to study the effectiveness of the proposed DIP framework.

II. DISASTER INFORMATION PROVIDER FRAMEWORK

EWS sensors continuously observe disturbances in the environment to receive inputs and accordingly generate warnings for any impending disasters. This paper proposes an innovative DIP framework (Figure 1) to better combat disasters in future. The objective of the framework is to rank the disaster affected regions with respect to 4 key elements of people-centric EWS, i.e. (i) Risk Knowledge (RK), (ii) Dissemination and Communication (DC), (iii) Monitoring and Warning Service (MWS), and (iv) Response Capability (RC) [10]. Each of these criteria (elements) is governed by multiple sub-criteria. Although these criteria and their sub-criteria are closely woven, sometimes they may get conflict [11]. We used the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a popular Multi-Criteria Decision-Making (MCDM) technique, which balances good results of some criteria with bad results of others, with the objective of minimizing the distance from the ideal case and maximizing the distance from the worst case [12]. A decision matrix, consisting of several alternatives (options) and sub-criteria (attributes) along with their weights is used as input in MCDM techniques. It ranks the alternatives with respect to sub-criteria in a real-world MCDM problem, e.g., ranking different car models on the basis of price, speed, and engine displacement. TOPSIS has also been applied to rank companies' stock and determine priorities of stock purchase for investment [13]. Authors in [14] report that for effective decision-making during a crisis, choosing the appropriate risk analysis approach within the maritime transportation is essential. With the aim to minimize training rejection returns, authors in [15] used TOPSIS to provide prioritized accreditation training process model based on internal and external criteria established by the National Agency for Evaluation and Quality Assurance of Higher Education and Training [15]. Its applicability to project selection process for non-profit organizations having two sternly related factors viz. restricted budget and social aspects, proves its potency [16]. It has also been used in fields like evaluating green performance of suppliers [17] and improving human resource management [18]. Further, to obtain better ranking of alternatives, the literature suggests various variants of TOPSIS, with the aim to reduce Rank Reversal Problem (RRP) and to assign appropriate weights to the criteria/sub-criteria. An RRP is a variation in the rank ordering of the alternatives when additional/existing alternatives are added/deleted [19]. Authors in [20] rank disaster affected regions using TOPSIS and suggested the use of variants of MCDM techniques and exploring refined sub-criteria for enhanced safety ranking and disaster preparedness [20].

The proposed DIP framework uses a novel TOPSIS variant to obtain enhanced ranking. The DIP consists of three units: (i) Sub-Criteria Analyzer, (ii) Weight Analyzer, and (iii) Ranking Unit. The functionality of three units of the DIP framework is described below.

A. Sub-Criteria Analyzer

A key to any successful disaster management plan is choosing the right combination of decision criteria for the current situation. Several user-defined sub-criteria associated with a disaster may be conflicting to each other, so it is important to categorize them carefully under key elements of the EWS to make informed quality decisions [21]. The first element of the EWS is RK which establishes a systematic, standardized process to collect, assess and share data, maps, and trends on hazards. The second element, DC, is responsible for ensuring that people and communities are warned of an impending disaster, and facilitate coordination and information exchange at regional and/or national level. The third element, MWS, establishes an effective hazard monitoring and warning service with a sound scientific and technological basis. The fourth element, RC, strengthens the ability of communities to respond to natural disasters by educating them about hazard risks, community participation, and disaster preparedness [22].

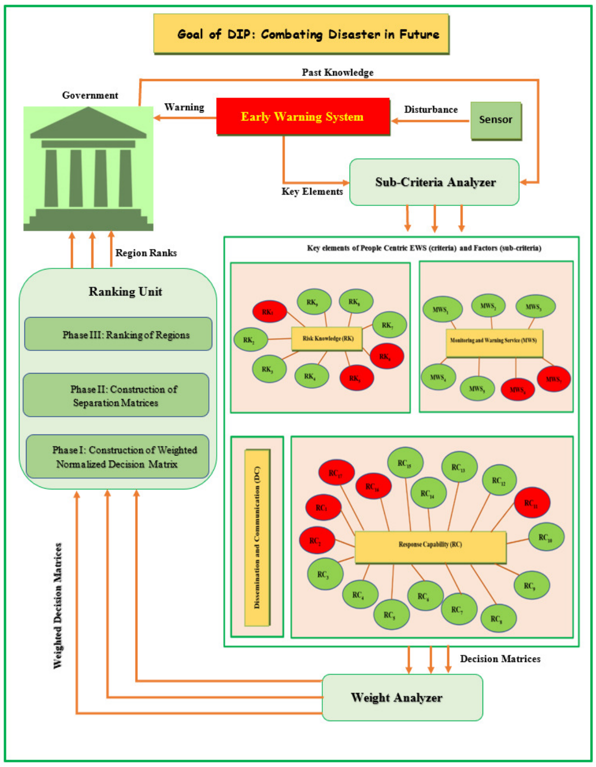

Fig. 1. The Disaster Information Provider (DIP) framework.

Authors in [23] highlight the importance of considering current data as well as past knowledge of EWS to handle disasters effectively. The Sub-Criteria Analyzer integrates information regarding the prior and the recent disasters in terms of user-defined sub-criteria to strengthen the key elements of the people-centric EWS. Using the past data, it reallocates the existing multiple sub-criteria related to disasters under the 4 key elements of the people-centric EWS and delivers 4 corresponding Decision Matrices (DMs), with rows as regions and columns as sub-criteria. Note that, in Figure 1, every user-defined sub-criterion has not been categorized to the DC element due to the absence of their direct association. Further, red and green sub-criteria signify cost and benefit sub-criteria, which is a required input for TOPSIS to be operational (see Appendix I).

B. Weight Analyzer

The four DMs corresponding to each key element of the EWS serve as input to the Weight Analyzer for computing the weights of the sub-criteria. These weights are used to construct 4 weighted DMs which serve as input to the Ranking Unit. The weight Analyzer computes sub-criteria weights using the entropy metric (see (1a), (1b)). Literature suggests that entropy-based weights methods are better than others because they avoid RRP [24].

$$V_j = -\frac{1}{\log m}\sum_{i=1}^{m}\frac{X_{ij}}{\sum_{i=1}^{m}X_{ij}}\log\frac{X_{ij}}{\sum_{i=1}^{m}X_{ij}} \quad (1a)$$

$$R_j = \frac{1-V_j}{\sum_{j=1}^{n}(1-V_j)} \quad (1b)$$

where R_j indicates the resilience (weight) of m regions on sub-criterion j, such that $\sum_{j=1}^{n} R_j = 1$, V_j indicates the vulnerability (entropy) of m regions on sub-criterion j, $0 \leq V_j \leq 1$, and X_{ij} is the performance value of region i on the sub-criterion j.

C. Ranking Unit

The Ranking Unit (Figure 2) deploys a novel TOPSIS variant, for ranking the regions considering the past performance of regions along with current performance of regions during catastrophes. It is executed in three phases, with two inputs, decision matrix $[X]$ and weight W_j, for each sub-criterion j, to output the rank of regions obtained as per the score of TOPSIS variant. For each EWS element, a region with low rank is implied to have outstanding disaster preparedness for that element.

Phase I starts with the normalization of the input DM $[X]$ using max-linear normalization to avoid RRP [24]. Subsequently, the weights (resilience) of the sub-criteria are multiplied with $[X]$ to obtain the performance of each region DM $[Y]$ with respect to the overall performance of DIP on each sub-criterion. Phase II computes two separation vectors namely a hypothetically best (S^+) and worst (S^-) solution set [25] to identify the best solution which is not only closest to the best possible solution, but also the farthest from the worst possible solution [20]. In order to get the hypothetical best solution S^+, the maximum value for the benefit criterion Y_j^+ and the minimum value for the cost criterion Y_j^- from m regions are considered. Similarly, the hypothetical worst solution S^- corresponds to negative ideal (worst) criteria values in $[Y]$ where benefit criterion Y_j^+ takes the lowest value while the cost criterion Y_j^- takes the highest. Further, separation vectors S_i^+ and S_i^- are obtained for each region i from its corresponding positive and negative ideal solutions respectively. Euclidean distance is used for the calculation of the separation vectors due to its popularity and simplicity over other distance measures [25, 26]. The computed separation vectors for each region i are used in phase III, to decide their ranking based on their distance from the optimized ideal reference point O. It is found that irregularities occur in traditional TOPSIS due to calculations of positive and negative ideal solutions using relative distance measure [27]. Instead of calculating the relative closeness to the positive ideal solution, the Ranking Unit obtains the absolute closeness to the positive ideal solution (C_i^+) and the absolute farness from the negative ideal solution (F_i^-) for each region i. The idea is to get a solution that is closest to the ideal reference point O, so that the absolute rank score A_i for each region i is the closest to the positive ideal reference point and the farthest from the negative ideal reference point. The smaller the value of A_i, the closer is C_i^+ to point O and the farther is F_i^- to point O. Thus, the regions are ranked in increasing order of A_i. The Ranking Unit is executed four times to obtain four different ranks of a region, with each rank corresponding to a unique element of the EWS. Note that non-numerical factors (qualitative scales) of EWS, if any, are converted into quantitative ones before providing the input to the Ranking Unit. A numerical example detailing the three phases of the Ranking Unit is shown in Appendix II.

Input: $[\boldsymbol{X}]$: DM where X_{ij} is the performance value of region i on the sub-criterion j. $\boldsymbol{R_j}$ weights indicating the resilience of m regions on sub-criterion j, such that $\sum_{j=1}^{n} R_j = 1$
Output: Dict *D* with regions ranked in increasing order of A_i.
Process of the Ranking Unit:
// Phase I: Computing Weighted Normalized DM $[Y]$
// Normalizing Decision matrix $[X]$
For X_{ij} in $[X]$ do
$if\ j \in J^+ then\ X_{ij} = \frac{X_{ij}}{X_j^{max}} \quad else\ X_{ij} = 1 - \frac{X_{ij}}{X_j^{max}}$
// J^+: {set of user-specified benefit sub-criteria}
// J^-: {set of user-specified cost sub-criteria}
For each element X_{ij} in $[X]$ do
$Y_{ij} = R_j * X_{ij}$
// Phase II: Construction of Separation Vectors
// Set $\{S^+\}$ and $\{S^-\}$ indicates hypothetical positive and negative ideal solution for each region
For Y_j in $[Y]$ do
$if\ j \in J^+ then\ Y_j^+ = \max(Y_{ij})\ else\ Y_j^+ = \min(Y_{ij})$
$\{S^+\} = \{S^+\}$^ Y_j^+
For Y_j in $[Y]$ do
$if\ j \in J^+ then\ Y_j^- = \min(Y_{ij})\ else\ Y_j^- = \max(Y_{ij})$
$\{S^-\} = \{S^-\}$^ Y_j^-
//Compute Separation Vectors (S_i^+ & S_i^-) for each region
For Y_i in $[Y]$ do
$S_i^+ = \sum_j \sqrt{\sum(Y_{ij} - Y_j^+)^2}$
$S_i^- = \sum_j \sqrt{\sum(Y_{ij} - Y_j^-)^2}$
//Phase III Ranking of Regions
// create empty dictionary to store regions with their corresponding score
D= { }
// Point O indicates optimized ideal reference point
Let $O(C_P, F_N)$; $C_P = min(S^+)\ and\ F_N = max(S^-)$
For each region i do
$C_i^+ = S_i^+ - C_P$
$F_i^- = S_i^- - F_N$
// C_i^+ is the absolute closeness of region i to positive ideal solution
// C_i^- is the absolute farness metric of region i to negative ideal solution
$A_i = \sqrt{[C_i^+]^2 + [F_i^{-2}]}$
// A_i is the score of the region i considering its closeness and farness from ideal solution
D.update(i, A_i)
Sort the dictionary D in increasing order of scores.

Fig. 2. Rankin Unit pseudo code.

III. EXPERIMENTAL PART

In order to demonstrate the utility of the novel DIP framework, we used Python 3 for coding and DKG report for the dataset [9]. Usability of DIP framework is initially shown by testing the efficacy of the Sub-Criteria Analyzer in sub-section A, followed by validating the performance of the Ranking Unit in sub-section B. The ranks obtained by the proposed DIP framework are discussed in sub-section C. We intend to work on sensitivity analysis in the future for signifying the use of vulnerability and resilience in the Weight Analyzer.

A. Efficacy of the Sub-Criteria Analyzer using EWS Criteria

The Sub-Criteria Analyzer allocates 34 sub-criteria [9] as per the definition of the four key elements of the people-centric EWS [22]. This allocation resulted into three DMs, each corresponding to a component of the EWS representing performance value. In each matrix, a row represents a region and a column indicates a sub-criterion. Each cell in the matrix shows the performance value of a sub criterion for a region (alternative). Mapping of sub-criteria is detailed in Appendix I.

Nine sub-criteria were categorized under the RK class, reflecting prior knowledge of the risk faced by the communities, with 6 of them as benefit sub-criteria and 3 as cost sub-criteria. Seven fall under the MWS class emphasizing on technical monitoring and warning services in the disaster-prone region. Considering the economic stability of the disaster affected region, 2 sub-criteria were classified as cost whereas 5 were taken as benefit sub-criteria. The rest of the 17 sub-criteria relate to the preparedness and the capability of the communities to cope up with disaster in the affected regions, so they were classified under the RC class of the EWS. Four were used as cost and 13 as benefit sub-criteria. In the absence of a direct association of any of the given 34 sub-criteria with the DC element, this element is not used while ranking. The Ranking Unit of the DIP framework is executed for each of the performance matrices to obtain rankings of all regions at level 1. Hence, each region is assigned 3 ranks, where the rank of a particular region reflects the performance of the region with respect to a particular key element of the EWS. Ranks for regions at level 2, 3 and 4 are not calculated due to the unavailability of data in the DKG report.

The 3 ranks for each region obtained by the Ranking Unit were aggregated for comparing the efficacy of the Sub-Criteria Analyzer with that of the DKG categorization. The Spearman rank correlation of the aggregated ranks was computed with that of DKG rank. In order to validate the efficacy of the Sub-Criteria Analyzer, the obtained results were compared with those of the DKG-TOPSIS (see Table I). Further, the average Mean Absolute Error (MAE) and Root Mean Squared error (RMSE) were computed to measure the net error score for each of the three key elements. The EWS-TOPSIS method was found to perform slightly better, clearly indicating that the ranking reported in the DKG report was preserved when the Sub-Criteria Analyzer allocated sub-criteria using the EWS categorization. Lower values of the metrics for EWS-TOPSIS confirm the enhanced performance of the Sub-Criteria Analyzer deploying EWS categorization. We recommend the use of RMSE in strengthening EWS as it is more sensitive to outliers leading to avoidance of large errors in predicted scores.

TABLE I. COMPARISON OF SUB-CRITERIA ANALYZER WRT DKG-TOPSIS AND EWS-TOPSIS

Error Value/ Rank Correlation	DKG-TOPSIS	EWS-TOPSIS
Average MAE	0.19	0.14
Average RMSE	0.22	0.09
Spearman rank correlation	0.85	0.88

B. Validating the Performance of the Ranking Unit

The ranks of the disaster affected regions at levels 1 are computed by employing 6 standard benefit criteria as mentioned in the DKG report using the Ranking Unit (RU-TOPSIS) and by using the traditional TOPSIS method (T-TOPSIS). Average MAE and RMSE were also calculated to measure the errors in the predicted scores by RU-TOPSIS and T-TOPSIS methods using the actual DKG scores along with Spearman rank correlation (Table II). Lower error values for RU-TOPSIS compared to T-TOPSIS and higher values of rank correlation vindicate the capability of the Ranking Unit in generating scores nearly close to the DKG scores. Hence, that variant of TOPSIS used in Ranking Unit seems promising for ranking disaster affected regions efficiently.

TABLE II. COMPARISON OF RANKING WITH RESPECT TO T-TOPSIS AND RU-TOPSIS

Error Value/ Rank Correlation	T-TOPSIS	RU-TOPSIS
Average MAE	0.27	0.15
Average RMSE	0.31	0.11
Spearman rank correlation	0.83	0.86

C. Discussion on the Ranks obtained by the Proposed DIP Framework

The results presented above depict that the proposed DIP framework is effective for understanding the preparedness of regions for combating similar disasters in future. The ranks obtained by DIP for regions of level I with respect to each key element of EWS are shown in Table III. Regions with higher scores compared to the DKG report should concentrate more on pre-disaster preparedness with respect to that particular key element of the EWS. Precisely, Switzerland (CH) and Israel (IL) should pay heed to all the three elements of EWS although they were ranked first in the DKG framework. Improved ranks for Netherlands (NL), Saudi Arabia (SA), and Vietnam (VN) compared to DKG ranks reveal better preparedness and hence, must pursue existing strategies to excel further. Countries like Canada (CA), Denmark (DK), New Zealand (HU), and Singapore (SG) should re-evaluate the strategies to strengthen the RC element of EWS. The line graph plotted in Figure 3 uses the scores computed by the components for better visualization of the preparedness as per the EWS framework. It is visible that most of the countries, excluding China (CH) and Vietnam (VN), are aware of RK. However, all except Austria (AT) fallback on MWS criteria. Intermediate scores for RC reveal further strengthening of the adopted strategies for combating the disaster by all countries, excluding Japan (JP) and Korea (KA).

TABLE III. REGION RANKS AS PER KEY ELEMENTS OF EWS

Region	Rank				Region	Rank			
	DKG	RK	MWS	RC		DKG	RK	MWS	RC
AU	8	6	15	14	NL	19	13	11	17
AT	6	8	1	13	NZ	9	12	3	15
CA	12	10	10	16	NO	14	11	18	18
CN	7	19	9	5	SA	17	16	17	11
DK	15	7	12	20	SG	4	3	2	8
DE	2	1	19	3	KR	10	9	20	4
HK	13	17	4	6	CH	1	5	8	2
HU	18	14	14	19	TW	16	18	7	9
IL	3	4		7	AE	11	15	13	10
JP	5	2	6	1	VN	20	20	16	12

Australia (AU), Austria (AT), Canada (CA), China (CN), Denmark (DK),, Germany (DE), Hong Kong (HK), Hungary (HU), Israel (IL), Japan (JP), Netherlands (NL), New Zealand (NZ), Norway (NO), Saudi Arabia (SA), Singapore (SG), South Korea (KR), Switzerland (CH), Taiwan (TW), United Arab Emirates (AE), Vietnam (VN)

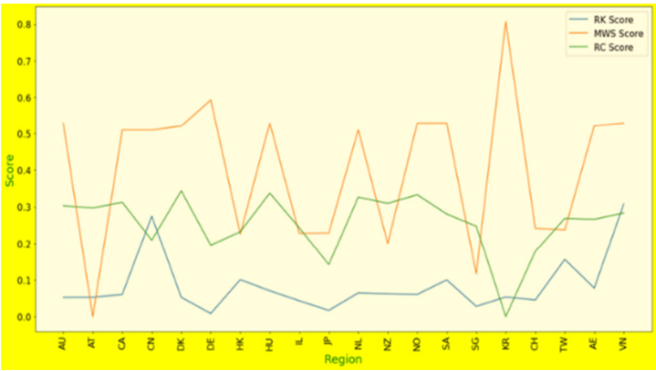

Fig. 3. Comparison of the scores obtained by the three key elements of the EWS.

IV. CONCLUSION

To better train governments to fight disasters like COVID-19 there is a need to reinforce key elements of a people-centric Early Warning System (EWS). Inspired by this, the authors propose a Disaster Information Provider (DIP) framework with the goal of ranking disaster-affected regions based on their past performance under the key elements of the EWS. The obtained ranking provided by DIP identifies weak elements of EWS in a specific region, allowing policymakers to plan more operative tactical strategies to fight future pandemics. The proposed DIP framework is a stand-alone model and can work for different disasters by modifying the input data to the Sub-Criteria Analyzer, such as reducing the risk accompanying with cyclones and sidestepping the probable damages due to tsunamis.

APPENDIX I

TABLE IV. CATEGORIZATION OF SUB-CRITERIA UNDER KEY ELEMENTS OF EWS

Criteria/ Sub-Criteria Type	Name	Description
Risk Knowledge: RK		
RK_1	Geopolitical vulnerabilities	Region's political instability based on its economic & military strength.
RK_2	Economic sustainability	Region's capacity to remain economically sustainable after pandemic.
RK_3	Previous national emergency experience	Emergencies focusing on preparation policies and government-led emergency relief efforts.
RK_4	Societal emergency resilience	Resilience, preparedness, past history, psychological/cultural/religious attitudes.
RK_5	Chronic diseases	Geographic risk in terms of proximity to infection prone areas, # border crossings, number of # population dense areas.
RK_6	Infection spread risk	Number of citizens prone to risk of getting infected with covid.
RK_7	Level of modern sanitization methods	Poor sanitization higher risk
RK_8	Covid-19 equipment availability	Total and per capita emergency equipment stockpiles.
RK_9	Epidemiology system level of development	Epidemiology system of a region in terms of quantity, distribution and sophistication.
Monitoring and Warning Service: MWS		
MWS_1	Monitoring & disaster management	Sophisticated surveillance and monitoring technologies.
MWS_2	Government surveillance technology	Monitoring infection rate & compliance with quarantine measures.
MWS_3	Reliability and transparency of data	Reliability of reported statistics.
MWS_4	Scope of diagnostic methods	Diverse diagnostic techniques and their effectiveness
MWS_5	AI for diagnostics and prognostics	Usage of AI analysis of results reducing the manpower needed.
MWS_6	Scale of quarantine	Lockdown/social distancing.
MWS_7	Quarantine timeline	How early quarantine measures are taken.
Response Capability: RC		
RC_1	Economic and supply chain freezing	Freeze via lockdown.
RC_2	Travel restrictions	Restrictions on citizens and tourists.
RC_3	Economic support for quarantines	Support for citizen's capacity to stay at home.
RC_4	Criminal penalties for violating quarantine	Presence and severity of region's criminal penalties for violation.
RC_5	Mobilization of new healthcare resources	Region's preparedness to mobilize additional healthcare resources.
RC_6	Quantity and quality of medical staff	Education and expertise
RC_7	Level of healthcare progressiveness	Quality of medical treatment
RC_8	Level of technological advancement	Sophistication/modernization/effectiveness of healthcare system.
RC_9	Testing efficiency	Time of testing and availability of lab personnel
RC_{10}	Culture specifics and societal discipline	Cultural and societal focus on health and sanitization
RC_{11}	Demography	Vulnerable demographics
RC_{12}	Level of security and defense advancement	To neutralize external threat
RC_{13}	Legislative efficiency	Deploying emergency response legislation (law)
RC_{14}	Rapid emergency mobilization	Capacity to mobilize emergency response
RC_{15}	Emergency military mobilization experience	Past experience of mobilizing military
RC_{16}	Efficiency of government structure	Effective governance to identify risk-prone regions
RC_{17}	Surveillance capabilities	Scale, scope and sophistication of surveillance capabilities.

* Considered as Cost in order to take care of the economic situation of a region.
** Considered as Cost as these activities may cause havoc among the people of a region.

APPENDIX II

Illustration of HU-TOPSIS on MWS Elements of EWS

Table V shows two inputs for the MWS element of EWS, namely the decision matrix $[\boldsymbol{X}]$ taken from the DKG report [9] and the sub-criterion weight ($\boldsymbol{R_j}$). Note that weights are calculated using (1b). In Phase I, the weight of each criterion ($\boldsymbol{R_j}$) is multiplied with the corresponding normalized values of $[\boldsymbol{X}]$ to obtain the weighted normalized decision matrix $[Y]$, shown in the same table. In Phase II, positive (S^+) and negative (S^-) ideal solutions are obtained and the values are shown as the last two rows in Table V. Subsequently, for each region, positive and negative separation distances (S_i^+ and S_i^-) are computed with respect to the ideal solutions (S^+, S^-), which are plotted in Figure 4. Here, the values of S_i^+ and S_i^- are plotted on the y-axis for all the regions plotted on the x-axis. It clearly shows that S_{AT}^+ attains minimum value among all the regions (shown in blue color). Also, S_{AT}^- attains maximum value among all the regions (shown in red color). Hence, Austria is closest to its positive ideal solution S_{AU}^+ and farthest from its negative ideal solution S_{AU}^-. So, it should be given rank 1. Likewise, S_{KR}^+ gets maximum value among all the regions (shown in blue color) and S_{KR}^- gets minimum value among all the regions (shown in red color), thereby making South Korea (KR) the farthest from its positive ideal solution and the closest to its negative ideal solution. So, it should be given the last rank. It is difficult to find the rank for regions like IL (Israel) and JP (Japan) by simply visualizing the graph in Figure 4. So, we move to phase III. On execution of RU-TOPSIS on level 1 regions, score A_i obtained is shown in Figure 5 with the corresponding ranks shown in red squares.

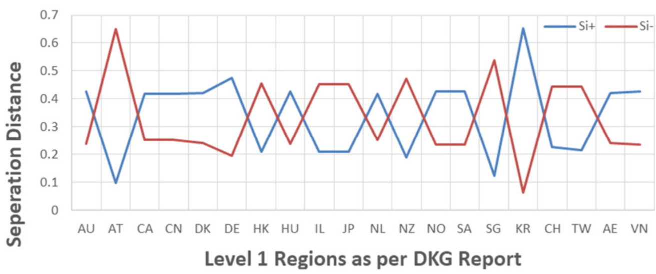

Fig. 4. Plot of S_i^+ and S_i^- obtained by RU-TOPSIS.

TABLE V. INPUT FOR THE RANKING UNIT AS PER THE MWS ELEMENTS OF THE EWS

Region	MWS_1		MWS_2		MWS_3		MWS_4		MWS_5		MWS_6		MWS_7	
AU	18	1	8.5	0.5	11.33	0.65	15	1	15	1	16.51	0.07	5.67	0.63
AT	18	1	8.5	0.5	11.33	0.65	15	1	15	1	16.64	0.07	15.67	0
CA	18	1	17	1	11.33	0.65	15	1	15	1	15.67	0.12	5.67	0.63
CN	12	0.6	17	1	11.33	0.65	15	1	15	1	17.91	0	5.67	0.63
DK	18	1	12.75	0.75	11.33	0.65	15	1	15	1	16.82	0.06	5.67	0.63
DE	18	1	13.6	0.8	17	0.98	15	1	15	1	16.51	0.07	4.25	0.72
HK	18	1	17	1	17.33	1	15	1	15	1	10.54	0.41	10.63	0.32
HU	18	1	8.5	0.5	11.33	0.65	15	1	15	1	17.75	0	5.67	0.63
IL	18	1	15.98	0.94	17	0.98	15	1	15	1	12.67	0.29	10.63	0.32
JP	18	1	15.3	0.9	17	0.98	15	1	15	1	17.81	0	10.63	0.32
NL	18	1	17	1	11.33	0.65	15	1	15	1	14.87	0.16	5.67	0.63
NZ	18	1	12.75	0.75	11.33	0.65	15	1	15	1	17.76	0	11.33	0.27
NO	18	1	8.5	0.5	11.33	0.65	15	1	15	1	14.34	0.19	5.67	0.63
SA	18	1	8.5	0.5	11.33	0.65	15	1	15	1	14.57	0.18	5.67	0.63
SG	18	1	14.96	0.88	17	0.98	15	1	15	1	13.65	0.23	12.75	0.18
KR	18	1	14.17	0.83	11.33	0.65	15	1	15	1	15.1	0.15	0	1
CH	18	1	9.18	0.54	17	0.98	15	1	15	1	15.36	0.14	10.63	0.32
TW	18	1	13.6	0.8	11.33	0.65	15	1	15	1	15.2	0.15	10.63	0.32
AE	18	1	13.6	0.8	8.5	0.49	15	1	15	1	15.75	0.12	5.67	0.63
VN	18	1	8.5	0.5	11.33	0.65	15	1	15	1	15.33	0.14	5.67	0.63
$\boldsymbol{R_j}$	0.015846		0.180596		0.116155		6.88E-15		6.88E-15		0.036619		0.650784	
$\{\boldsymbol{S^+}\}$	0.015846		0.180596		0.116155		6.88E-15		6.88E-15		0		0	
$\{\boldsymbol{S^-}\}$	0.010564		0.090298		0.056972		6.88E-15		6.88E-15		0.015069		0.650784	

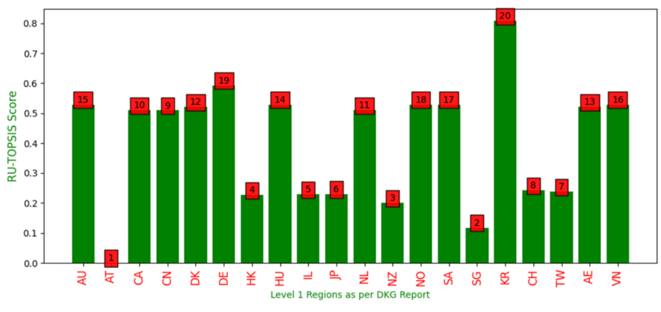

Fig. 5. RU-TOPSIS scores and ranks for level 1 regions for the MWS criteria of an EWS.

REFERENCES

[1] C. J. Winter, "Disaster? No surprise," *Environmental Politics*, vol. 31, no. 1, pp. 70–88, Jan. 2022, https://doi.org/10.1080/09644016.2020.1865726.

[2] M. Esposito, L. Palma, A. Belli, L. Sabbatini, and P. Pierleoni, "Recent Advances in Internet of Things Solutions for Early Warning Systems: A Review," *Sensors*, vol. 22, no. 6, Jan. 2022, Art. no. 2124, https://doi.org/10.3390/s22062124.

[3] "Early warning system | UNDRR," Aug. 30, 2007. http://www.undrr.org/terminology/early-warning-system.

[4] T. Kelhe, C. Jain, M. Bhandarkar, and A. Deshpande, "A Smart Early Warning System for Disease Outbreak with a Case Study of COVID-19 in India," in *IEEE Pune Section International Conference*, Pune, India, Dec. 2020, pp. 113–118, https://doi.org/10.1109/PuneCon50868.2020.9362380.

[5] A. H. S. Fang, W. T. Lim, and T. Balakrishnan, "Early warning score validation methodologies and performance metrics: a systematic review," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, Jun. 2020, Art. no. 111, https://doi.org/10.1186/s12911-020-01144-8.

[6] T. D. G. Hermans, R. Sakic Trogrlic, M. J. C. van den Homberg, H. Bailon, R. Sarku, and A. Mosurska, "Exploring the integration of local and scientific knowledge in early warning systems for disaster risk reduction: a review," *Natural Hazards*, vol. 114, no. 2, pp. 1125–1152, Nov. 2022, https://doi.org/10.1007/s11069-022-05468-8.

[7] W. Wang, T. Zhang, T. Yao, and B. An, "Monitoring and early warning system of Cirenmaco glacial lake in the central Himalayas," *International Journal of Disaster Risk Reduction*, vol. 73, Apr. 2022, Art. no. 102914, https://doi.org/10.1016/j.ijdrr.2022.102914.

[8] E. K. Ronoh, S. Mirau, and M. A. Dida, "Human-Wildlife Conflict Early Warning System Using the Internet of Things and Short Message Service," *Engineering, Technology & Applied Science Research*, vol. 12, no. 2, pp. 8273–8277, Apr. 2022, https://doi.org/10.48084/etasr.4662.

[9] DKG 2020, "COVID-19 Regional Safety Assessment." https://analytics.dkv.global/covid-regional-assessment-200-regions/full-report.pdf.

[10] EWC III, "Developing Early Warning Systems: A Checklist," in *Third International Conference on Early Warning*, Bonn, Germany, Mar. 2006.

[11] M. F. Abdullah, S. Siraj, and R. E. Hodgett, "An Overview of Multi-Criteria Decision Analysis (MCDA) Application in Managing Water-Related Disaster Events: Analyzing 20 Years of Literature for Flood and Drought Events," *Water*, vol. 13, no. 10, Jan. 2021, Art. no. 1358, https://doi.org/10.3390/w13101358.

[12] M. E. Banihabib, F.-S. Hashemi-Madani, and A. Forghani, "Comparison of Compensatory and non-Compensatory Multi Criteria Decision Making Models in Water Resources Strategic Management," *Water Resources Management*, vol. 31, no. 12, pp. 3745–3759, Sep. 2017, https://doi.org/10.1007/s11269-017-1702-x.

[13] E. S. Saleh and A. M. Kimiagari, "Ranking Tehran's Stock Exchange Top Fifty Stocks Using Fundamental Indexes and Fuzzy TOPSIS," *Engineering, Technology & Applied Science Research*, vol. 7, no. 4, pp. 1863–1869, Aug. 2017, https://doi.org/10.48084/etasr.1252.

[14] M. Mousavi, I. Ghazi, and B. Omaraee, "Risk Assessment in the Maritime Industry," *Engineering, Technology & Applied Science Research*, vol. 7, no. 1, pp. 1377–1381, Feb. 2017, https://doi.org/10.48084/etasr.836.

[15] N. Benmoussa, A. Elyamami, K. Mansouri, M. Qbadou, and E. Illoussamen, "A Multi-Criteria Decision Making Approach for Enhancing University Accreditation Process," *Engineering, Technology & Applied Science Research*, vol. 9, no. 1, pp. 3726–3733, Feb. 2019, https://doi.org/10.48084/etasr.2352.

[16] A. R. Radhi and A. M. Burhan, "Non-Profit Organization Project Selection Process Using the Hygiene Method of Multi-Criteria Decision Making," *Engineering, Technology & Applied Science Research*, vol. 12, no. 5, pp. 9097–9101, Oct. 2022, https://doi.org/10.48084/etasr.5175.

[17] K. R. Ramakrishnan and S. Chakraborty, "A cloud TOPSIS model for green supplier selection," *Facta Universitatis, Series: Mechanical Engineering*, vol. 18, no. 3, pp. 375–397, Oct. 2020, https://doi.org/10.22190/FUME200307036R.

[18] U. Rahardja, N. Lutfiani, S. Sudaryono, and R. Rochmawati, "The Strategy of Enhancing Employee Reward Using TOPSIS Method as a Decision Support System," *Indonesian Journal of Computing and Cybernetics Systems*, vol. 14, no. 4, pp. 387–396, Oct. 2020, https://doi.org/10.22146/ijccs.58298.

[19] B. Yang, J. Zhao, and H. Zhao, "A robust method for avoiding rank reversal in the TOPSIS," *Computers & Industrial Engineering*, vol. 174, Dec. 2022, Art. no. 108776, https://doi.org/10.1016/j.cie.2022.108776.

[20] S. Hezer, E. Gelmez, and E. Ozceylan, "Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment," *Journal of Infection and Public Health*, vol. 14, no. 6, pp. 775–786, Jun. 2021, https://doi.org/10.1016/j.jiph.2021.03.003.

[21] H. Maleki and S. Zahir, "A Comprehensive Literature Review of the Rank Reversal Phenomenon in the Analytic Hierarchy Process," *Journal of Multi-Criteria Decision Analysis*, vol. 20, no. 3–4, pp. 141–155, 2013, https://doi.org/10.1002/mcda.1479.

[22] WMO, "Multi-hazard Early Warning Systems: A Checklist," in *Outcome of the first Multi-hazard Early Warning Conference*, Cancun, Mexico, Dec. 2017, pp. 1–20.

[23] D. Baneres, M. E. Rodriguez, A. E. Guerrero-Roldan, and A. Karadeniz, "An Early Warning System to Detect At-Risk Students in Online Higher Education," *Applied Sciences*, vol. 10, no. 13, Jan. 2020, Art. no. 4427, https://doi.org/10.3390/app10134427.

[24] R. F. de F. Aires and L. Ferreira, "The rank reversal problem in multi-criteria decision making: A literature review," *Pesquisa Operacional*, vol. 38, no. 2, pp. 331–362, Aug. 2018, https://doi.org/10.1590/0101-7438.2018.038.02.0331.

[25] P. Talukdar and P. Dutta, "A Comparative Study of TOPSIS Method via Different Distance Measure," *International Journal of Research in Advent Technology*, vol. 7, no. 5, pp. 118–126, Jun. 2019, https://doi.org/10.32622/ijrat.75201937.

[26] R. F. de F. Aires and L. Ferreira, "A new approach to avoid rank reversal cases in the TOPSIS method," *Computers & Industrial Engineering*, vol. 132, pp. 84–97, Jun. 2019, https://doi.org/10.1016/j.cie.2019.04.023.

[27] W. Yang, "Ingenious Solution for the Rank Reversal Problem of TOPSIS Method," *Mathematical Problems in Engineering*, vol. 2020, Jan. 2020, Art. no. e9676518, https://doi.org/10.1155/2020/9676518.