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 $Y^+$ and the minimum value for the cost criterion $Y^-$ from $m$ regions are considered. Similarly, the hypothetical worst solution $S^-$ corresponds to negative ideal (worst) criteria values in $[Y]$ where benefit criterion $Y^+$ takes the lowest value while the cost criterion $Y^-$ 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: $[X]$: DM where $x_{ij}$ is the performance value of region $i$ on the sub-criterion $j$. $R_j$ 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 $[Y]$
// Normalize Decision matrix $[X]$
For $X_{ij}$ in $[X]$ do
if $j \in J^+$ then $Y_{ij}^+ = \frac{x_{ij}}{\max (x_{ij})}$
else $Y_{ij}^+ = \frac{x_{ij}}{\max (x_{ij})}$
// $J^+$: (set of user-specified benefit sub-criteria)
// $J^-$: (set of user-specified cost sub-criteria)
For each element $X_{ij}$ in $[X]$ do
$Y_{ij} = R_j \times X_{ij}$

// Phase II: Construction of Separation Vectors
// Set ($S^+$) and ($S^-$) indicates hypothetical positive and negative ideal solution for each region
For $Y_i$ in $[Y]$ do
if $j \in J^+$ then $Y_i^+ = \max (Y_{ij})$
else $Y_i^+ = \min (Y_{ij})$
// ($S^+$) = ($S^+$) $\cup$ $Y_i^+$
For $Y_i$ in $[Y]$ do
if $j \in J^-$ then $Y_i^- = \min (Y_{ij})$
else $Y_i^- = \max (Y_{ij})$
// ($S^-$) = ($S^-$) $\cup$ $Y_i^-$

// Compute Separation Vectors ($S_i^+$ & $S_i^-$) for each region
For $Y_i$ in $[Y]$ do
$S_i^+ = \sum_{j=1}^{n} (Y_{ij} - Y_i^+)^2$
$S_i^- = \sum_{j=1}^{n} (Y_{ij} - Y_i^-)^2$

// Phase III Ranking of Regions
// Create empty dictionary to store regions with their corresponding score
$D = \{\}$
// Point $O$ indicates optimized ideal reference point
Let $O(C_p, F_k); C_p = \min (S^+)$ and $F_k = \max (S^-)$
For each region $i$ do
$C_i^+ = S_i^+ - C_p$
$F_i^- = S_i^- - F_k$
// $C_i^+$ is the absolute closeness of region $i$ to positive ideal solution
// $F_i^-$ 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. Ranking 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>
<thead>
<tr>
<th>Error Value/ Rank Correlation</th>
<th>DKG-TOPSIS</th>
<th>EWS-TOPSIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MAE</td>
<td>0.19</td>
<td>0.14</td>
</tr>
<tr>
<td>Average RMSE</td>
<td>0.22</td>
<td>0.09</td>
</tr>
<tr>
<td>Spearman rank correlation</td>
<td>0.85</td>
<td>0.88</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Error Value/ Rank Correlation</th>
<th>T-TOPSIS</th>
<th>RU-TOPSIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MAE</td>
<td>0.27</td>
<td>0.15</td>
</tr>
<tr>
<td>Average RMSE</td>
<td>0.31</td>
<td>0.11</td>
</tr>
<tr>
<td>Spearman rank correlation</td>
<td>0.85</td>
<td>0.86</td>
</tr>
</tbody>
</table>

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).
performance under the key elements of the EWS. The obtained the goal of ranking disaster-affected regions based on their past propose a Disaster Information Provider (DIP) framework with Early Warning System (EWS). Inspired by this, the authors 19 there is a need to reinforce key elements of a people-centric framework is a stand-alone model and can work for different specific region, allowing policymakers to plan more operative ranking provided by DIP identifies weak elements of EWS in a tsunamis.

cyclones and sidestepping the probable damages due to disasters by modifying the input data to the Sub-Criteria

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

<table>
<thead>
<tr>
<th>Criteria/Sub-Criteria</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Name</td>
</tr>
<tr>
<td>RK1</td>
<td>Geopolitical vulnerabilities</td>
</tr>
<tr>
<td>RK2</td>
<td>Economic sustainability</td>
</tr>
<tr>
<td>RK3</td>
<td>Previous national</td>
</tr>
</tbody>
</table>

![Fig. 3. Comparison of the scores obtained by the three key elements of the EWS.](image)

TABLE III. REGION RANKS AS PER KEY ELEMENTS OF EWS

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

Rank

RK4 Societal emergency resilience | Resilience, preparedness, past history, psychological/cultural/religious attitudes. |
RK5 Chronic diseases | Geographic risk in terms of proximity to infection prone areas, # border crossings, number of # population dense areas. |
RK6 Infection spread risk | Number of citizens prone to risk of getting infected with covid. |
RK7 Level of modern sanitization methods | Poor sanitization higher risk |
RK8 Covid-19 equipment availability | Total and per capita emergency equipment stockpiles. |
RK9 Epidemiology system level of development | Epidemiology system of a region in terms of quantity, distribution and sophistication. |

Response Capability: RC

RC1 Economic and supply chain freezing | Freeze via lockdown. |
RC2 Travel restrictions | Restrictions on citizens and tourists. |
RC3 Economic support for quarantines | Support for citizen’s capacity to stay at home. |
RC4 Criminal penalties for violating quarantine | Presence and severity of region’s criminal penalties for violation. |
RC5 Mobilization of new healthcare resources | Region’s preparedness to mobilize additional healthcare resources. |
RC6 Quantity and quality of medical staff | Education and expertise |
RC7 Level of healthcare progressiveness | Quality of medical treatment |
RC8 Level of technological advancement | Sophistication/modernization/effectiveness of healthcare system. |
RC9 Testing efficiency | Time of testing and availability of lab personnel |
RC10 Culture specifics and societal discipline | Cultural and societal focus on health and sanitation |
RC11 Demography | Vulnerable demographics |
RC12 Level of security and defense advancement | To neutralize external threat |
RC13 Legislative efficiency | Deploying emergency response legislation (law) |
RC14 Rapid emergency mobilization | Capacity to mobilize emergency response |
RC15 Emergency military mobilization experience | Past experience of mobilizing military |
RC16 Efficiency of government structure | Effective governance to identify risk-prone regions |
RC17 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.

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

<table>
<thead>
<tr>
<th>Region</th>
<th>MWS₁</th>
<th>MWS₂</th>
<th>MWS₃</th>
<th>MWS₄</th>
<th>MWS₅</th>
<th>MWS₆</th>
<th>MWS₇</th>
</tr>
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<tbody>
<tr>
<td>AU</td>
<td>18</td>
<td>1</td>
<td>8.5</td>
<td>0.5</td>
<td>11.33</td>
<td>0.65</td>
<td>15</td>
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<tr>
<td>AT</td>
<td>18</td>
<td>1</td>
<td>8.5</td>
<td>0.5</td>
<td>11.33</td>
<td>0.65</td>
<td>15</td>
</tr>
<tr>
<td>CA</td>
<td>18</td>
<td>1</td>
<td>17</td>
<td>1</td>
<td>11.33</td>
<td>0.65</td>
<td>15</td>
</tr>
<tr>
<td>CN</td>
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<td>11.33</td>
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<tr>
<td>DK</td>
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<td>12.75</td>
<td>0.75</td>
<td>11.33</td>
<td>0.65</td>
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<tr>
<td>DE</td>
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<td>13.6</td>
<td>0.8</td>
<td>17</td>
<td>0.98</td>
<td>15</td>
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<tr>
<td>HK</td>
<td>18</td>
<td>1</td>
<td>17</td>
<td>1</td>
<td>17.33</td>
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<td>15</td>
</tr>
<tr>
<td>HU</td>
<td>18</td>
<td>1</td>
<td>8.5</td>
<td>0.5</td>
<td>11.33</td>
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Fig. 5. RU-TOPSIS scores and ranks for level 1 regions for the MWS criteria of an EWS.

REFERENCES


