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Perceived Recovery Trajectories in Post-Earthquake Nepal – A Visual Exploration With Self Organizing Maps

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ABSTRACT Developing effective recovery plans requires an intricate understanding of the experiences of affected residents following a disaster event. We combined a self-organizing map (SOM) and hierarchical clustering to analyze community perceptions towards disaster response/recovery operations following the 2015 Nepal earthquake. A survey was conducted by the Inter-Agency Common Feedback Project (CFP) that includes six rounds of responses collected a month apart from the fourteen districts with the highest damage levels. The purpose of the survey was to identify gaps in disaster response, provide timely feedback, and enable stakeholders to address the gaps. Using the survey responses, we identified three satisfaction clusters among districts: 1) least satisfied, 2) moderately satisfied, and 3) highly satisfied. These clusters were used to visualize each district's satisfaction trajectory over the study horizon. Based upon their trajectories, we further classified the districts into three groups: 1) Recovering, 2) Not Recovering – Moderately Satisfied, and 3) Not Recovering – Least Satisfied. With the expansion of CFP's work across the entire humanitarian development cycle, the methodology highlighted in this paper could help stakeholders better understand the effectiveness of response actions to improve recovery planning.

INDEX TERMS Self-organizing maps, neural networks, Nepal earthquake, disaster recovery, community perception.

I. INTRODUCTION

Despite significant research on disaster recovery, it remains the most challenging and least understood phase of the disaster cycle [1]–[4]. Initially conceptualized as a linear process with a clearly defined sequence of activities to restore physical and social systems [5], disaster recovery is increasingly seen as a dynamic, non-linear process that varies across space and time [3], [6]–[8]. This new perspective has attracted an interdisciplinary group of researchers and elevated the importance of effective recovery planning [9]–[11].

Recent advancements in disaster recovery often link this phase with resilience, and newly proposed indicators are improving our understanding of recovery-resilience dynamics [1], [12], [13]. Other examples include Chang [4] who provides a framework to assess urban recovery using statistical indicators and offers a way to define recovery and make comparisons across different areas or disaster events. Finch *et al.* [14] investigate the differential recovery in New Orleans following Hurricane Katrina using the Social Vulnerability Index (SoVI) [15]. Horney *et al.*[16] propose a set of indicators to enable practitioners in the United States to document disaster recovery at the community level. Sutley & Hamideh [17] offer a multi-disciplinary perspective to understanding the complexities and interdependencies of the long-term housing recovery process.

A recent review by Mayer [18] underscores that researchers are now utilizing more subjective and bottom-up methods for understanding recovery. Jones [19] emphasizes the importance of subjective measures to understanding context-specific resilience and proposes an assessment tool that could complement existing objective. The use of Big Data and Artificial Intelligence (AI) is another emerging area in recovery research. Shibuya and Tanaka [20] use social media data and sentiment analysis to identify socio-economic

TABLE 1. Estimated % of Population Directly Affected By Housing Damage From the 2015 Earthquake in the 14 Crisis-Hit Districts of Nepal [30]

Districts	% Population Affected	Districts	% Population Affected
Bhaktapur	27.6	**Makwanpur**	17.4
Dhading	59.2	**Nuwakot**	97.9
Dolakha	100	**Okhaldhunga**	30.9
Gorkha	67.2	**Ramechhap**	60.9
Kathmandu	8.5	**Rasuwa**	72.3
Kavrepalanchok	61.9	**Sindhuli**	31.6
Lalitpur	14.9	**Sindhupalchowk**	95.9

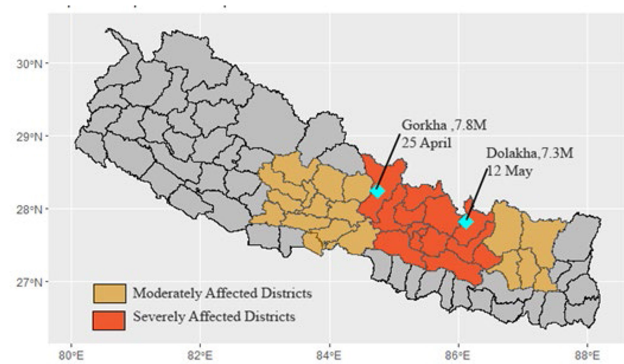

FIGURE 1. Map of Nepal showing the epicenters of the 2015 Nepal earthquake and affected area [33].

recovery following the East Japan Earthquake and Tsunami of 2011.

The goal of this paper is to illustrate how subjective measures can be combined with Machine Learning (ML) to identify perceived recovery trajectories following a major disaster. We apply a Self-Organizing Map (SOM) and hierarchical clustering algorithm to a survey conducted following the 2015 Nepal earthquake to visualize longitudinal change in recovery perceptions. The survey contains numerous variables related to disaster victims' perceptions (Table 3), many of which may be correlated. Dimensionality reduction could be helpful in identifying significant patterns in the indicators of recovery perceptions. SOM is a computational method for dimensionality reduction that has advantages over traditional statistical methods due to its ability to facilitate easy identification of non-linear relationships among variables [21]. SOM has recently been applied in speech recognition [22], flood hazard modeling [23], and land use land cover changes [24]. An early spatial application of SOM was to visualize changes in socio-economic data [25]. Delmelle *et al.* [21] used SOM to study urban neighborhood changes using quality of life indicators. A recent study by Chen *et al.* [26] used SOM to visualize disaster risk in China at a regional level.

II. 2015 NEPAL EARTHQUAKE

Nepal was hit by a catastrophic earthquake of 7.8M on 25th April 2015 with epicenter in Gorkha district. Numerous aftershocks followed for several months, but the most significant was the 7.3M quake of the 12th of May with epicenter in Dolakha district. These twin earthquakes (Fig. 1) and their aftershocks affected more than 8 million people in 39 of 75 districts [27]. About 9000 people lost their lives, and 22000 were injured [28]. Nepal incurred a financial loss of about one-third of its Gross Domestic Product (GDP) [29]. Fourteen districts that accounted for more than 80% of total housing damage were designated as crisis-hit districts. Humanitarian agencies worldwide responded, and financial assistance poured in to help with relief and recovery.

The humanitarian cluster system was activated [30] within a month of the first earthquake to coordinate national and international response. Hubs were designated to ensure coordination at the local level. According to the consolidated agency tracker from the Nepal office of the United Nations (UN) Office for the Coordination of Humanitarian Affairs (OCHA), 426 non-governmental organizations worked in the 39 affected districts under ten different clusters: Camp Coordination and Management (CCCM), Early Recovery, Education, Emergency Telecommunications (ETC), Food, Health, Nutrition, Protection, Shelter, and Water, Sanitation and Hygiene (WASH) between May and June 2015 [31]. The shelter cluster alone had more than 300 partner organizations on the ground providing shelter assistance in the form of cash, Non-Food Items (NFI), labor, shelter materials, or winterization [30].

Damage from the earthquake was uneven throughout the districts (Table 1) and the response disproportionate. Shelter Cluster Nepal [30] noted that, as the earthquake event continued to be referred to as the "Gorkha Earthquake", the "high-damage, high-profile" districts such as Gorkha and Sindhupalchowk received disproportionately greater consideration leading to an uneven response. The scenario in Nepal resembled the post-disaster recovery process as characterized by Peacock *et al.* [32], "requiring an immense influx of resources, highly uneven, and expected to reinforce rather than address the preexisting vulnerabilities."

III. METHODOLOGY

A. DATA

CFP was launched in the earthquake aftermath to assess the effectiveness of relief operations and disaster victims' perceptions of response actions [34]. CFP randomly selected approximately 100 participants from each of the 14 severely affected districts and administered monthly surveys from July to December 2015 (Table 2). The intent was to provide timely feedback to the partners so that the gaps in response could be addressed. The original survey dataset included nine questions with minor variation among rounds. The dataset used in our research is an aggregate of possible responses to seven consistent questions (six earthquake-related and one demographic) from those six rounds (R1 – R6). The survey questions, answer choices, and resulting SOM input variables are listed in Table 3. The count data for a total of 52 answer choices

TABLE 2. Total Number of Survey Respondents in Each of the 14 Crisis-Hit Districts During the Six Survey Rounds (R1-R6)

Districts	R1 (July)	R2 (Aug)	R3 (Sept)	R4 (Oct)	R5 (Nov)	R6 (Dec)
Bhaktapur	103	100	100	100	100	100
Dhading	99	100	100	100	100	100
Dolakha	101	101	100	100	100	100
Gorkha	97	101	100	100	100	100
Kathmandu	97	99	100	100	100	100
Kavrepalanchok	99	100	100	100	100	100
Lalitpur	105	100	100	100	100	100
Makwanpur	103	99	100	100	100	100
Nuwakot	101	99	100	100	100	100
Okhaldhunga	0	100	100	100	100	100
Ramechhap	99	100	100	100	100	100
Rasuwa	100	100	100	100	100	100
Sindhuli	101	100	100	100	100	100
Sindhupalchowk	99	99	100	100	100	100
Total Responses	**1304**	**1398**	**1400**	**1400**	**1400**	**1400**

corresponding to the survey questions are converted into a percentage of total response per district per round for SOM analysis.

B. SELF-ORGANIZING MAPS

Kohonen [35] developed SOM, an artificial neural network, to project input data of higher dimensions onto a lower-dimensional attribute space while preserving the topological characteristics of the data. SOM places observations with similar attributes closer together and dissimilar observations further apart using a two-dimensional grid architecture of input and output nodes. Each node in the grid has a processing unit "neuron" connected to adjacent units by a neighborhood function. Data with similar attributes are mapped to proximal nodes.

To train a SOM, each neuron is initialized with a set of weights, one per input variable. At each iteration, a randomly selected observation from the training set is presented to the grid. Spatially organized maps are then generated in two steps. First, the algorithm calculates the similarity between each observation and each node. For example, while using Euclidean similarity measure, the distance between each attribute in the selected observation and the corresponding weight at each node are calculated and then summed to get a total distance. Lower the distance, higher the similarity and vice versa. Second, the observation is assigned to the best matching unit or a node with the highest similarity to the observation. Then, the weight of the best matching unit is updated toward the value of the vector by a small amount, and the nodes within its neighborhood are adjusted accordingly. This concurrent adjustment of weights helps generate maps ordered in output space [35]. The algorithm then selects another observation and repeats this process until all observations have been compared to the SOM grid. The algorithm is repeated over many iterations, until the organization of observations on the grid stabilizes.

TABLE 3. Summary of the Survey Questions, Answer Choices for Each Question and Corresponding SOM Variable

Question	Answer Choices	SOM Variable
What is your biggest problem?	Clean water	prb_water
	Education	prbl_edu
	Financial support	prb_fin
	Food	prb_food
	Healthcare	prb_hlth
	Housing inspections	prb_insp
	Livelihoods	prb_lvl
	Long term shelter / housing	prb_ltslt
	N.A.	prb_na
	Others	prb_oth
	Psychosocial counseling	prb_psyc
	Seeds and fertilizers	prb_agri
	Short-term shelter (tent / shelterbox)	prb_stshltr
	Toilets / sanitation	prb_sani
Are your main problems being addressed?	1 Not at all	addr_1
	2 Very little	addr_2
	3 Neutral	addr_3
	4 Mostly yes	addr_4
	5 Completely yes	addr_5
	6 Don't know	addr_6
	7 Refused	addr_7
What is the top thing that you need information about?	Finding missing people	inf_miss
	How to get healthcare psychosocial support	inf_psyc
	How to get shelter materials	inf_slt
	How to register for access support	inf_admin
	How to replace personal documentation	inf_docs
	N.A.	inf_na
	News about government decisions	inf_news
	Others	inf_oth
Are you satisfied with what NGOs are doing for you after the earthquake?	1 Not at all	ngo_1
	2 Very little	ngo_2
	3 Neutral	ngo_3
	4 Mostly yes	ngo_4
	5 Completely yes	ngo_5
	6 Don't know	ngo_6
	7 Refused	ngo_7
Is support provided in a fair way?	1 Not at all	fair_1
	2 Very little	fair_2
	3 Neutral	fair_3
	4 Mostly yes	fair_4
	5 Completely yes	fair_5
	6 Don't know	fair_6
	7 Refused	fair_7
Do you have any health problems?	Not at all	hlth_1
	Yes, some	hlth_2
	Yes, a lot	hlth_3
	Cannot do at all	hlth_4
Occupation	Farmer / Laborer	occ_frm
	Government (i.e., teacher, health worker, army)	occ_gov
	NGO Worker / Business	occ_ngo
	Other	occ_oth
	Skilled Worker (i.e., Carpenter)	occ_skill

An important consideration in SOM training is selecting the size of the output grid. With a small number of nodes, the SOM algorithm works in a similar way to cluster analysis. As the grid size increases, the resulting SOM starts to represent the underlying topology of the observations. In this study, this represents a state space of possible recovery conditions. This is analogous to the dimension reduction in principal component analysis. However, as the SOM allows for non-linear organization of observations, it allows for the emergence of a more complex topology, including unimodal and multimodal variable distributions and changing correlations between variables [21].

For this study, we used a 9 by 6 grid, which is slightly greater than that given by the rule-of-thumb $5*\sqrt{N}$ (N= number of observations) proposed by Vesanto and Alhoniemi [36]. This allows for the emergence of structure as well as clustering of similar observations. We used packages "kohonen" [37] and "colorspace" [38] for SOM training and visualizations in the R environment [39]. Neurons were initialized with a random set of weights. Default values of the Kohonen package were used for the parameters learning rate and radius. Over 2000 iterations, learning rate declined linearly from 0.05 to 0.01, and default radius changed linearly to zero from a value that covers two-thirds of all unit-to-unit distances.

C. HIERARCHICAL CLUSTERING

Hierarchical clustering is an algorithm that groups similar nodes on the SOM grid into distinct clusters. Agglomerative hierarchical clustering is the most common technique, where each node is initially treated as an individual cluster, and at each iteration, the algorithm identifies the two closest clusters and merges them. Samsonova *et al.* [40] used hierarchical clustering with SOM to help in interpretability simplifying the topology further into a small set of groups whose characteristics can be directly and simply compared. Other examples using hierarchical clustering with a SOM include [41] and [42].

IV. RESULTS

A. SOM TRAINING

As mentioned in Section III.A, pre-processing of the perception dataset produced 84 observations (14 districts by 6 rounds) with 54 attributes (52 from total answer choices and the remaining two for districts and rounds, respectively). Since there were no responses from the Okhaldhunga District in the first round, the row was eliminated, and the remaining 83 rows were used to train the SOM. Each district, therefore, is attributed to a node of the SOM grid six times, except for Okhaldhunga.

Fig. 2 shows changes in the loss function or the Average Quantization Error (AQE), which represents the mean distance between node weights and observations assigned to that node. The algorithm converged at around 1600 iterations. Fig. 3(a) shows the number of observations in each node. The dark grey nodes do not have any associated observations and represent infilling of the parameter space. The nodes with single observations are towards the center, and denser nodes are spread outwards. The neighbor distance plot (Fig. 3(b)) reveals an interesting pattern. Nodes with a higher distance between neighbors are arranged in a diagonal line from bottom left to top center, representing a distinction between observations on the two sides. Nodes on the left appear to bear more resemblance to the neighboring nodes than those on the right as there are outliers, and the distance between nodes is comparatively larger.

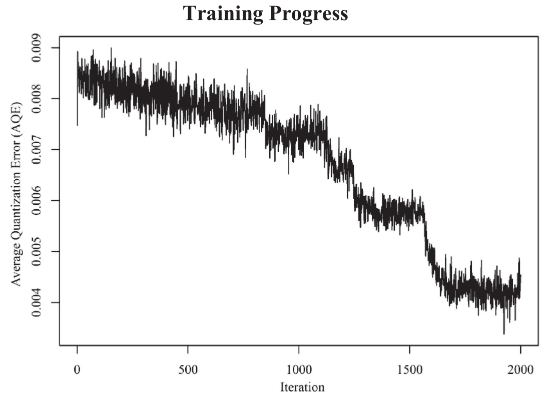

FIGURE 2. Training progress. SOM algorithm converged at around 1600 iterations.

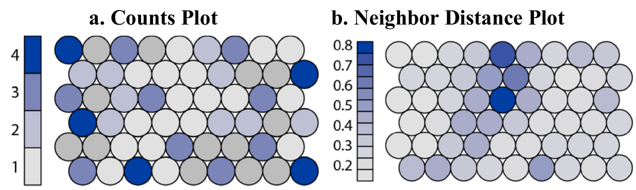

FIGURE 3. a) Number of observations in each node. Dark gray circles represent the empty nodes. b) Plot showing the average distance of each node to its neighbors.

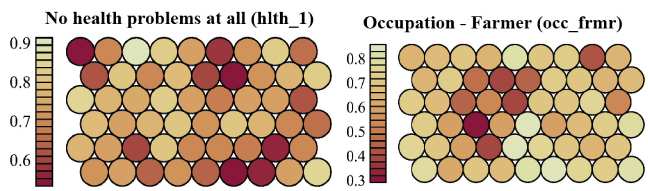

FIGURE 4. Component plane visualizations for the variables ("hlth_1") and ("occ_frmr").

B. ANALYSIS OF VARIABLES

SOM allows for mapping each variable's relative contribution towards the overall organization of the nodes in the output space. These visualizations, referred to as component planes, are among the most significant output of SOM training, as we can discern the non-linear and partial correlations among input variables [21]. We plotted the importance of each of the 52 variables given in Table 3. We determine that the variables for the questions 'Do you have any health problems?' and 'Occupation' were not very significant. Component planes for the variables 'health_1' and 'occ_frmr' are given in Fig. 4. These do not exhibit a clear pattern and have higher weights, indicating that a majority of the respondents were farmers, and a significant proportion of respondents did not report any significant health problems.

The component plane visualizations for the most important variables are given in Figs. 5–9, broken down by their respective question categories. The scale on the left indicates the weights assigned to nodes. For positive variables' prb_na', 'addr_4', 'addr_5', 'inf_na', 'fair_4', 'fair_5', 'ngo_4', and

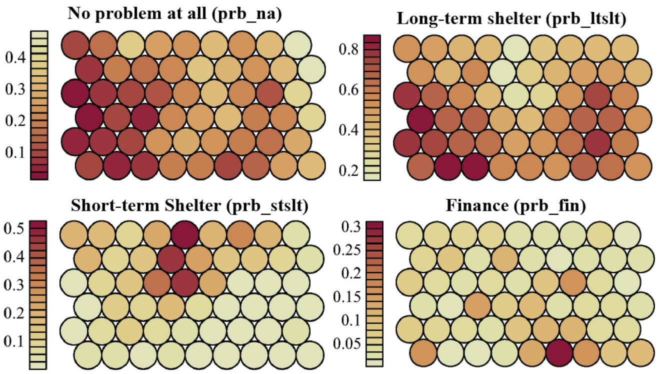

FIGURE 5. Most important variables in the question category ("What is your biggest problem?").

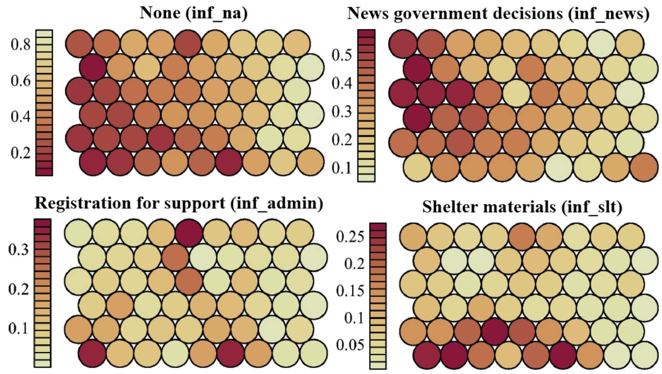

FIGURE 7. Most important variables in the question category ("What is the top thing that you need information about?").

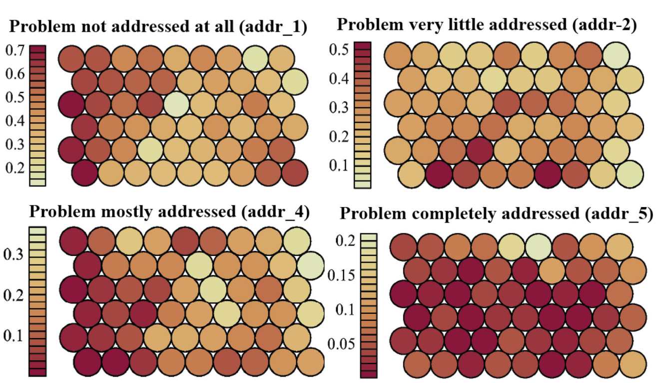

FIGURE 6. Most important variables in the question category ("Are your problems being addressed?").

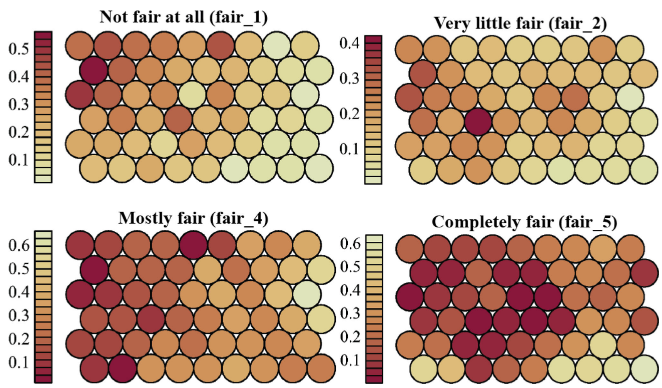

FIGURE 8. Most important variables in the question category ("Is support provided in a fair way?").

'ngo_5', lower weights are shown in red and higher weights in light yellow. The color ramp is reversed for negative variables to improve visual consistency. The gradient from red to light yellow represents the continuum from higher perception of problems and lower satisfaction to lower perception of problems and higher satisfaction.

These visualizations reveal that the observations are distinctly ordered in SOM space which helps to identify partial and non-linear correlations among the variables. For example, the first component plane in Fig. 5 shows an overall perception of problems. The gradient from bottom left to top right represents a decreasing perception of having problems. This plot is visually similar to the plots for variables 'addr_1', 'addr_4' (Fig. 6) 'inf_na' (Fig. 7), 'fair_4' (Fig. 8), and 'ngo_4' (Fig. 9), indicating that the perception of problems and the problems not being addressed are inversely related to the perception of fairness and satisfaction towards the activities of non-government organizations (NGOs). Furthermore, these component planes partially correlate with the component planes for the variables 'prb_ltslt', 'inf_news', and 'inf_slt' indicating that the perception of problems is higher in the areas with greater long-term shelter needs, lower access to information about news regarding government decisions, and accessing shelter materials.

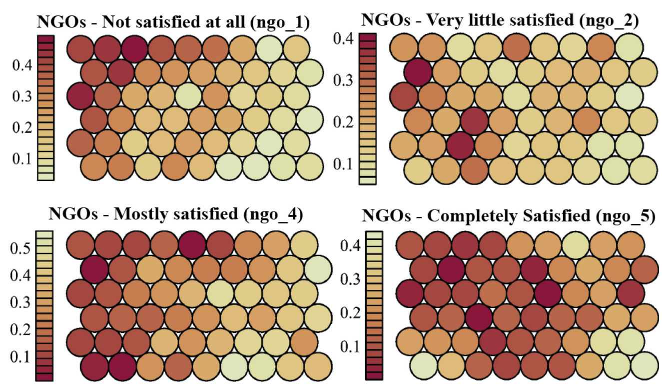

FIGURE 9. Most important variables in the question category ("Are you satisfied with what NGOs are doing for you after the earthquake?").

We can also identify outliers from the component planes. For example, when we look at the first two plots in Fig. 5, it can be descerned that the long-term shelter is the greatest concern in the areas with highest perception of problems. However, the remaining two component planes show nodes where the issues of short-term shelter and finance are prominent. Identification of such outliers could be helpful for stakeholders to investigate further and provide targeted responses.

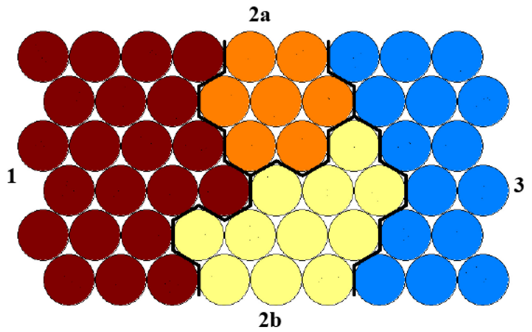

FIGURE 10. Cluster of nodes resulting from application of hierarchical clustering algorithm to the output node.

C. CLUSTER ANALYSIS

Simply showing the nodes where each district landed during the six rounds of the survey does not provide a meaningful basis for interpretation. Therefore, a hierarchical clustering analysis with "Ward.D2" algorithm is applied on the SOM output to aggregate nodes into homogenous clusters based on their similarities (Fig. 10). Based on the visual interpretation of the neighbor distance plot (Fig. 3(b)) and variables plot (Figs. 5–8), four clusters explain the data the best, as the nodes at the center are distinct from the nodes on the left and right. There is also a distinction between the top and bottom nodes in the center.

We plotted the cluster map showing the variables with the highest weight in each node (Fig. 11). However, only the variables deemed significant from our analysis are shown (Figs. 5–9). For example, the node on the bottom-left corner had the highest weight for 'occ_frmr' variable and the second highest weight for 'addr_1' variable. Therefore, the node is labeled 'addr_1' with a rank of two. Similarly, if the variable considered significant is the highest rank, it is labeled as such with a rank of one.

1) CLUSTER 1: LEAST SATISFIED

This least satisfied cluster is the largest one and characterized by the greatest perceived problems, information inequity, and least satisfaction regarding the efforts of NGOs and other agencies to address the issues. This cluster appears to be the least informed about government decisions and accessing shelter materials. Most respondents in this cluster believe their problems are not being addressed, and they report the least perceived fairness and satisfaction regarding the recovery efforts.

2) CLUSTER 2: MODERATELY SATISFIED

2a. Type I - This is the smallest cluster of moderately satisfied nodes that exhibit the most significant distinction among clusters in the top problem category. While other clusters perceive long-term shelter as the foremost concern, this cluster is more concerned with short-term shelter. Regarding information needs, nodes on this cluster seem to be the most diverse as evident from the variables plot (Fig. 7). Among seven nodes in this cluster, two have higher weight for 'inf_ news' variable, three have higher weights for 'inf_admin' variable and one has higher weight for 'inf-slt' variable.

2b. Type II - This cluster of moderately satisfied nodes perceives long-term shelter and financial problems as top concerns. News about government decisions is the top information needed, followed by access to the shelter materials and registration for support.

3) CLUSTER 3: MOST SATISFIED

This final cluster has the highest access to information and exhibits the greatest satisfaction toward the efforts targeted to address their problems. While the least satisfied and moderately satisfied clusters had a wide range of problems, almost all the problems in this cluster can be attributed to long-term shelter.

D. PERCEPTION TRAJECTORIES

We then identified the nodes where each district was attributed for each of the six rounds of survey and traced the path across the SOM grid. The series of plots in Fig. 12 show the trajectories of each of the fourteen districts in the study area from round 1 through round 6. The clusters and trajectories of change are also visualized in the geographical maps (Fig. 13). Eight of the thirteen districts (no data was available for Okhaldhunga district for round 1) fell under cluster 1, and the remaining five fell under cluster 2 during the first round. While some districts exhibit a positive trend in recovery perception, some demonstrate very little change, and some change significantly without any notable improvement in perceived satisfaction. Based on perceived satisfaction trajectories, the districts are further classified into three categories:

1) RECOVERING

Seven out of fourteen districts, Dhadhing, Gorkha, Kathmandu, Okhaldhunga, Rasuwa, Sindhuli, and Sindhupalchowk fall under this category. Although these districts exhibit positive trends, there are some notable differences. For example, Gorkha, the epicenter of the earthquake, starts on the moderate satisfaction cluster, immediately jumps to the highest satisfaction cluster in the second round where it remains. However, Kathmandu, the capital of Nepal, remains in the least satisfied cluster for five survey phases before abruptly making a leap to the highest satisfaction cluster in the final round. Rasuwa and Sindhupalchowk, with similar trajectories, demonstrate the biggest positive change, starting from the top left corner of cluster 1 to the bottom right corner of cluster 4.

2) NOT RECOVERING – MODERATELY SATISFIED

Four districts, Bhaktapur, Lalitpur, Nuwakot, and Ramechhap, fall under this category. Although they exhibit temporal changes in recovery perceptions, their perceived satisfaction did not improve much by the end of the study period. Bhaktapur occupies six different nodes in six different rounds.

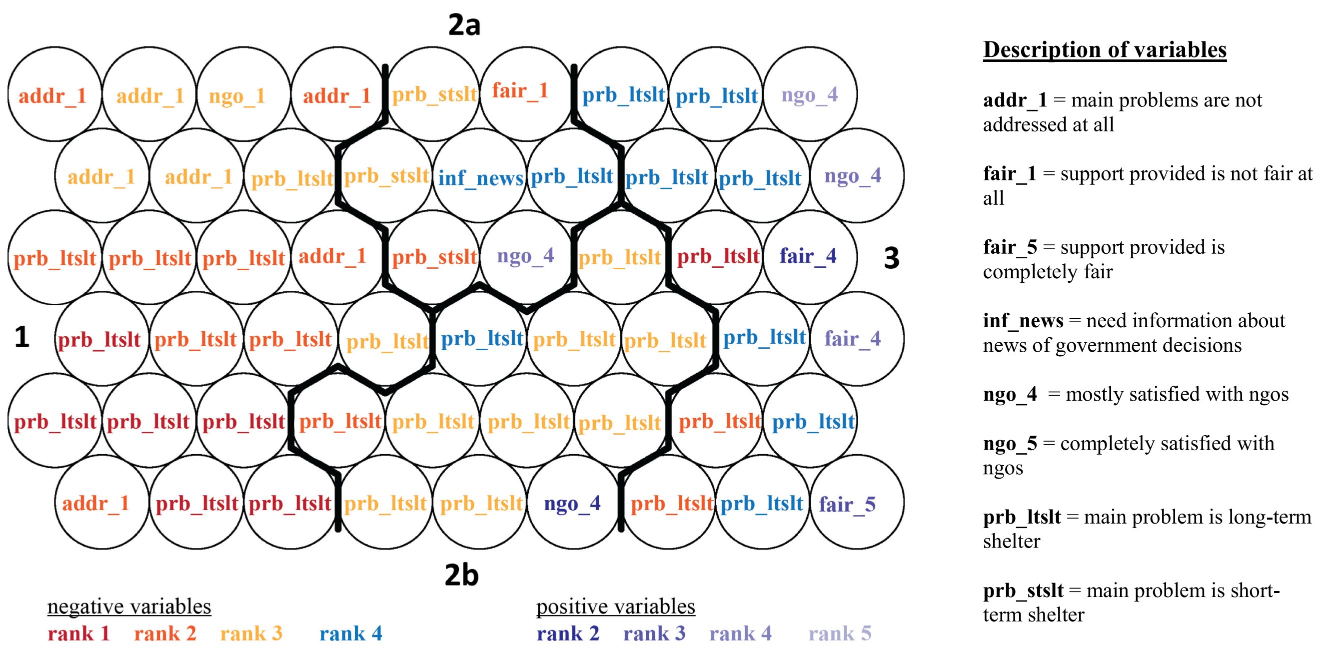

FIGURE 11. Significant variables with the highest weight in each node. Colors indicate the rank among all variables included in SOM analysis. From left to right, variables in the nodes transition from high-rank negative to low-rank positive, indicating the differences in perceptions of problems and recovery among different clusters.

The trajectory of Lalitpur is along the center of SOM output and traverses boundaries between each of the four clusters. Ramechhap starts at the top row of cluster 2, moves to the bottom-left node in cluster 1, and ends up in cluster 3. On the contrary, Nuwakot starts at the top-left node of cluster 1, moves to the boundary nodes of medium satisfaction clusters, and reverts to cluster 1 in round 6.

3) NOT RECOVERING – LEAST SATISFIED

Three remaining districts, Dolakha, Makwanpur, and Kavrepalanchok, fall under this category. These districts remain in cluster 1 (Least Satisfied) and show few changes across the 6 surveys, suggesting little improvement in conditions.

V. DISCUSSION

By and large, there was a positive trend in recovery perception in post-earthquake Nepal. The first survey was administered within three months of the earthquake and the districts started at somewhat similar territory of least or moderately satisfied clusters. The result is not very surprising given that the primary focus was on immediate response than long-term recovery. However, some distinct patterns emerged over the six rounds in the trajectories of districts.

Gorkha, the epicenter of the 7.8M earthquake, demonstrated the highest positive perception towards the support provided (Fig. 12(d)). Gorkha and Sindhupalchowk received very high media attention immediately after the first earthquake of April 25. More support might have reached these districts early on, leading to an overall higher positive perception of recovery. Nodes in variables plot (Fig. 5) corresponding to the trajectories for Gorkha and Sindhupalchowk demonstrate that Sindhupalchowk had higher perception of problems compared to Gorkha by the end of the survey period. Similarly, Rasuwa also had higher overall perception of problems and information disparity at the end of round 6 despite landing in the highest satisfaction cluster. Sindhupalchowk and Rasuwa had higher percentage of population affected by housing damage (Table 1) compared to Gorkha.

Dolakha and Nuwakot also had higher percentage of affected population than Gorkha, but they exhibit different trajectories. Dolakha suffered significant additional damages from the May 12 earthquake, and entire population of the district was estimated to be affected. This might have pushed the recovery perception in further negative territory during the second and third survey rounds (Fig. 12(c)). It is interesting to note that, Nuwakot, surrounded by districts with highest perceived satisfaction remained in the least satisfied cluster at the end of round 6 (Fig. 13(i)). The amount of aid received, or progress made by neighboring districts could also have an impact on the satisfaction.

Makwanpur and Kavrepalanchok are among the districts with least perceived satisfaction and least change. Closer examination of corresponding nodes in variables plot reveal that Makwanpur had lower perception of problems during the second half of the survey period (Fig. 5). Nonetheless, they were less satisfied with NGOs (Fig. 9) and had lower perception of fairness (Fig. 8). On the other hand, Kavrepalanchok

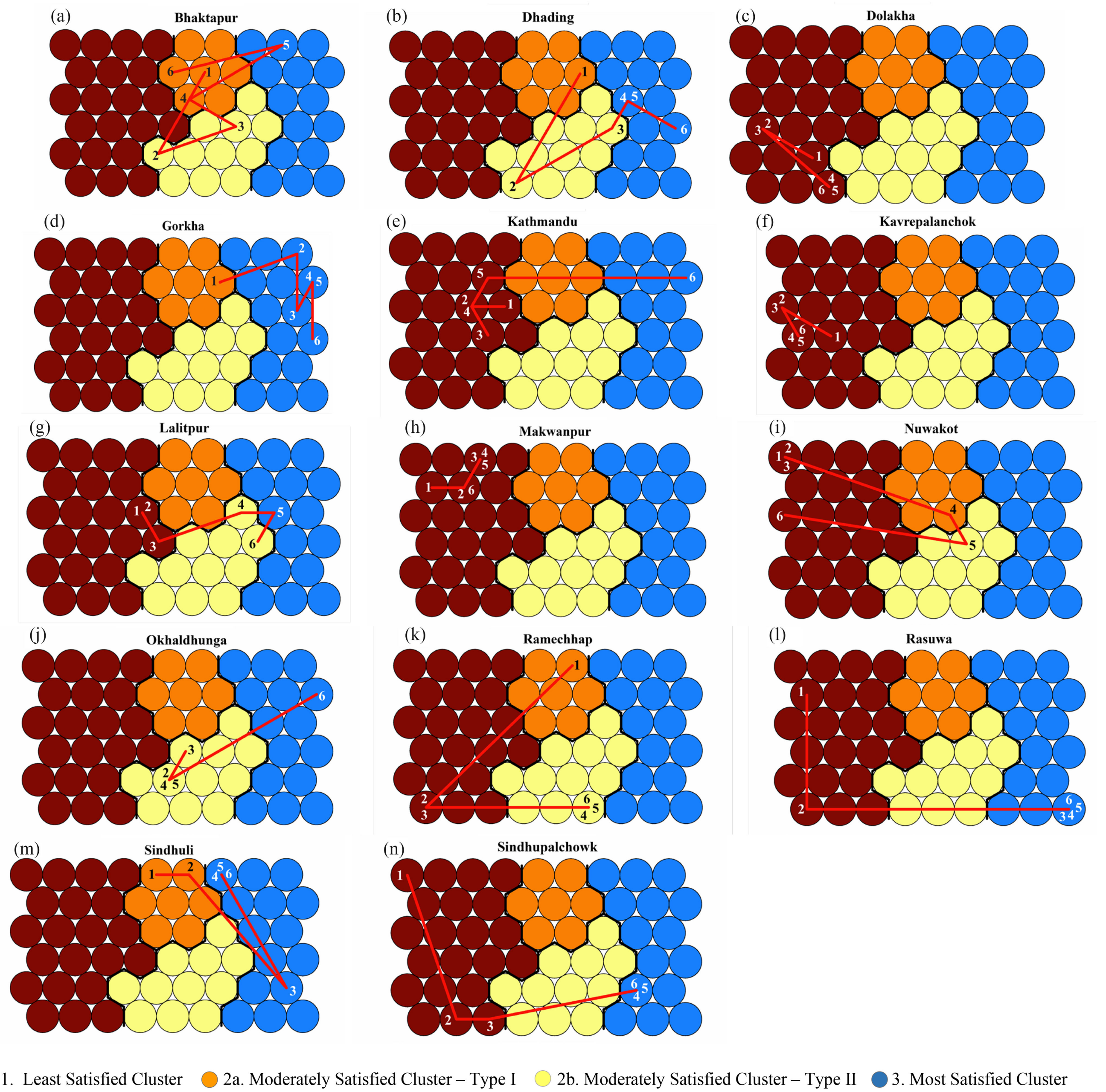

FIGURE 12. Recovery perception trajectories of 14 districts visualized in SOM space.

consistently demonstrated higher overall perception of problems, information inequity and dissatisfaction towards NGOs.

The three districts in Kathmandu Valley, Bhaktapur Kathmandu, and Lalitpur had pockets of severely damaged areas. These districts also have the lowest percentage of population affected. However, these are very densely populated districts in Nepal and the total housing damage is comparable to the districts with the highest percentage damage. These districts occupy the central space in the SOM output and show unique perception trajectories. Kathmandu Valley has nearly one quarter of the country's urban population, and recovery might have different meaning to the people in this area.

VI. CONCLUSION

Through SOM and cluster analysis, we demonstrated the recovery perception trajectories of the fourteen districts hardest hit by the 2015 Nepal earthquake. Our analysis shows that districts with similar damage levels could have different perceived trajectories and a one-size- fits-all approach of disaster response/recovery might not address all the issues of the disaster victims. An ethnographic study conducted by

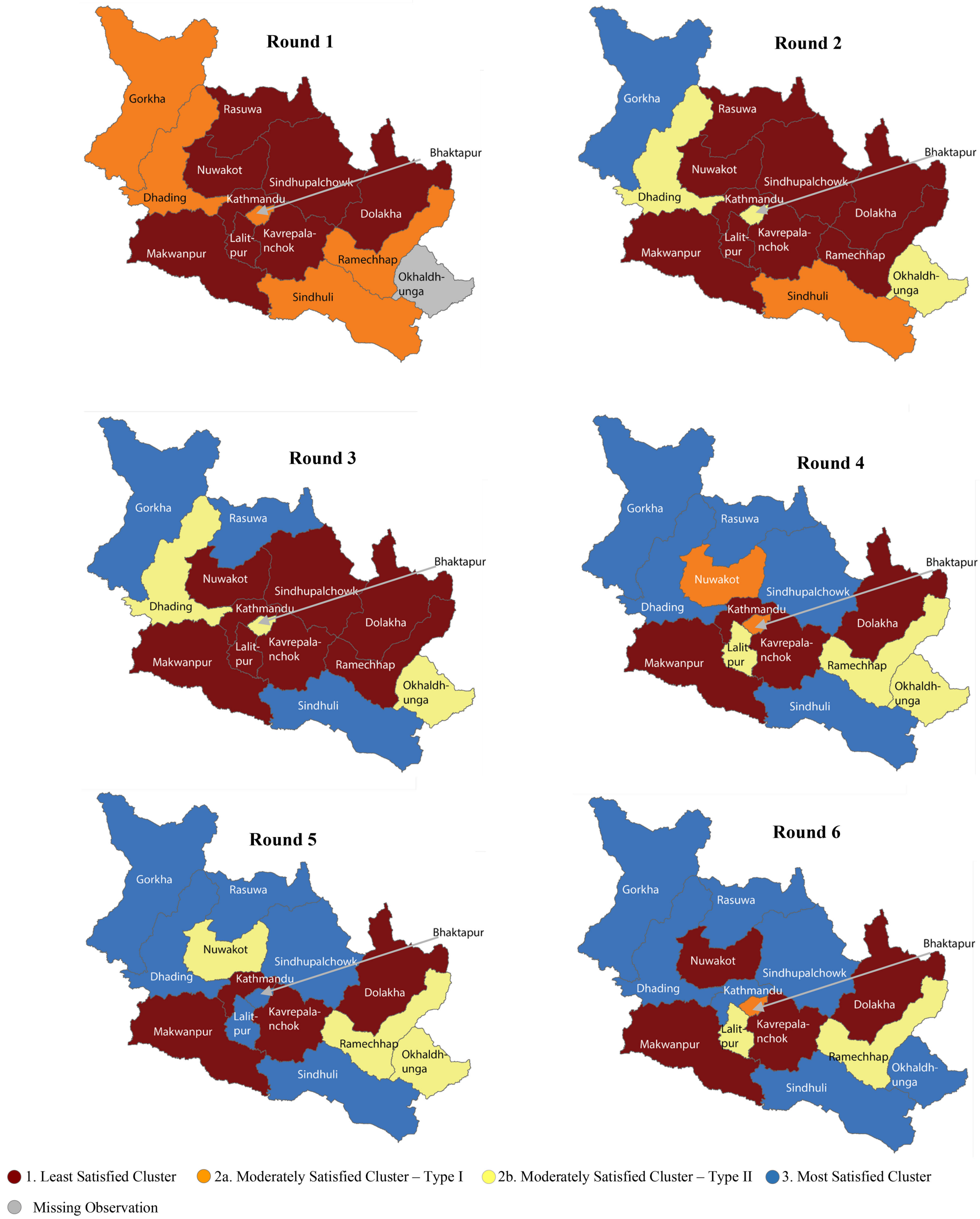

FIGURE 13. **Geographic visualization of temporal changes in recovery perception trajectories of the 14 districts.**

Spoon *et al.* [43] in Gorkha and Rasuwa districts following the earthquake identified socio-economic status, hazard exposure, livelihood, and displacement as the most significant indicators determining household-level recovery outcomes. It might be interesting to visualize these indicators in the SOM grid and identify any correlations to the recovery perceptions. Identifying factors leading to the observed patterns is beyond the scope of this exploratory research. However, future work could look at the timeline and amount of support provided, damage percentage, percentage of the total population affected in each district, along the effects of demographic and geographical factors.

In the context of Nepal, most of the government response was delegated through the smaller administrative units, Village Development Committees (VDCs), and the nongovernmental response was coordinated at the district level. SOM and cluster analysis could also be used for analysis at the VDC level to gain actionable insights and provide a more tailored response to the following stages of recovery or in case of future disasters. All datasets used in this study are from secondary sources, and it limited our ability to perform more structured analyses at finer spatial units and establish firm associations.

Disaster impacts vary among households in the same community and communities in the same district. Improving our understanding of disaster victims' perceptions and sharing this information with practitioners is essential for improving the recovery process. Thus, CFP has expanded its work to the entire humanitarian development cycle and across multiple disasters [44]. Although the damage assessments and perceptions surveys are conducted at the household level, it is virtually impossible to tailor the response at a finer scale. Therefore, disaster recovery studies, practitioners, and policymakers could benefit from a SOM that allows flexibility to delve into specific variables and identify correlations or generalizations in a concise and visually intuitive way.

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