The Application of ETC2.0 Probe Data and Network Clustering in Investigating Urban Mobility Patterns During an Extreme Snow Event

3-B-14

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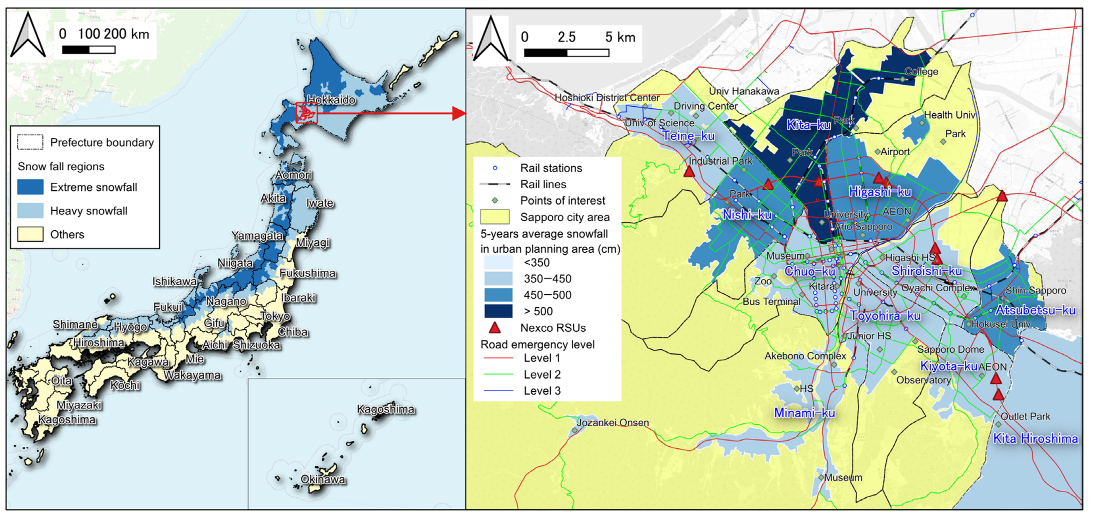
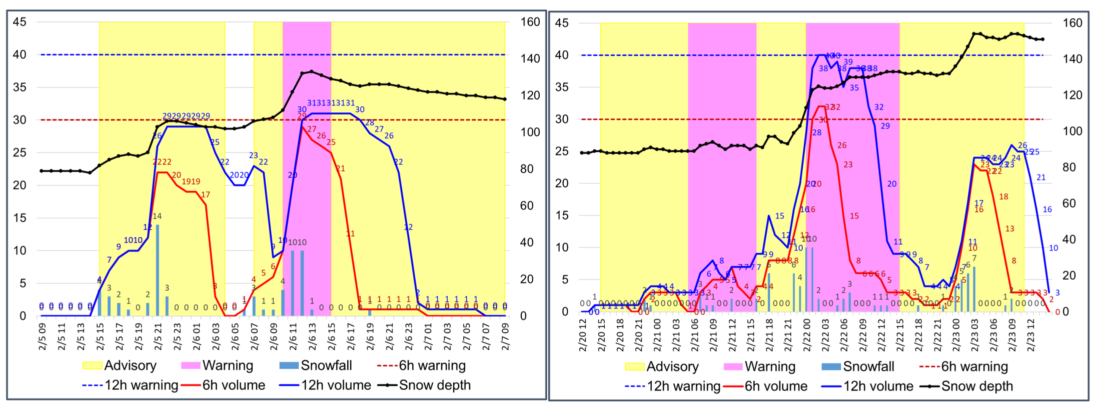
Introduction



- Japan has the largest population proportion living in cold regions globally.
- Large area in the country locate in heavy snowfall area.
- Historical snowfall events hit the Sapporo city in Feb, 2022



Transportation system situation

- Road congestion
- Trains suspended
- Bus delayed, canceled
- Aviation interrupted

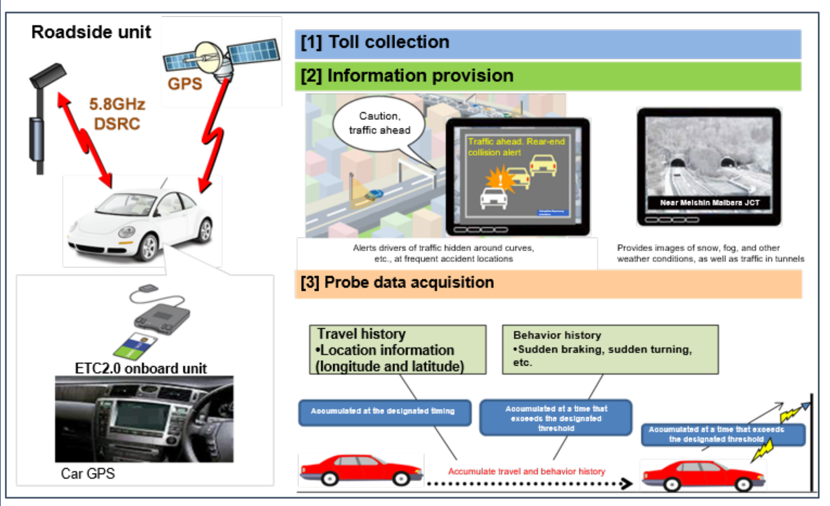
Effects

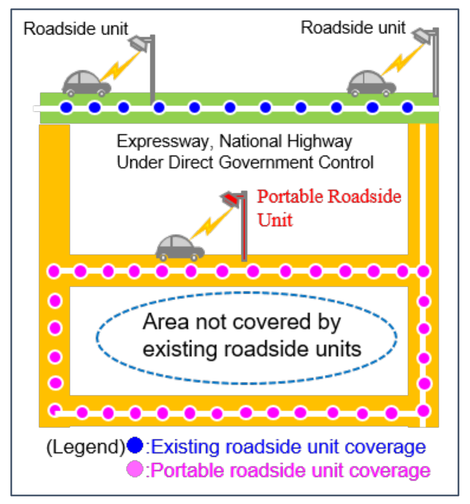
- Commuting disturbance
- Traffic accidents
- Stranded people at stations, airport
- Logistics services disrupted, etc.,

Purposes

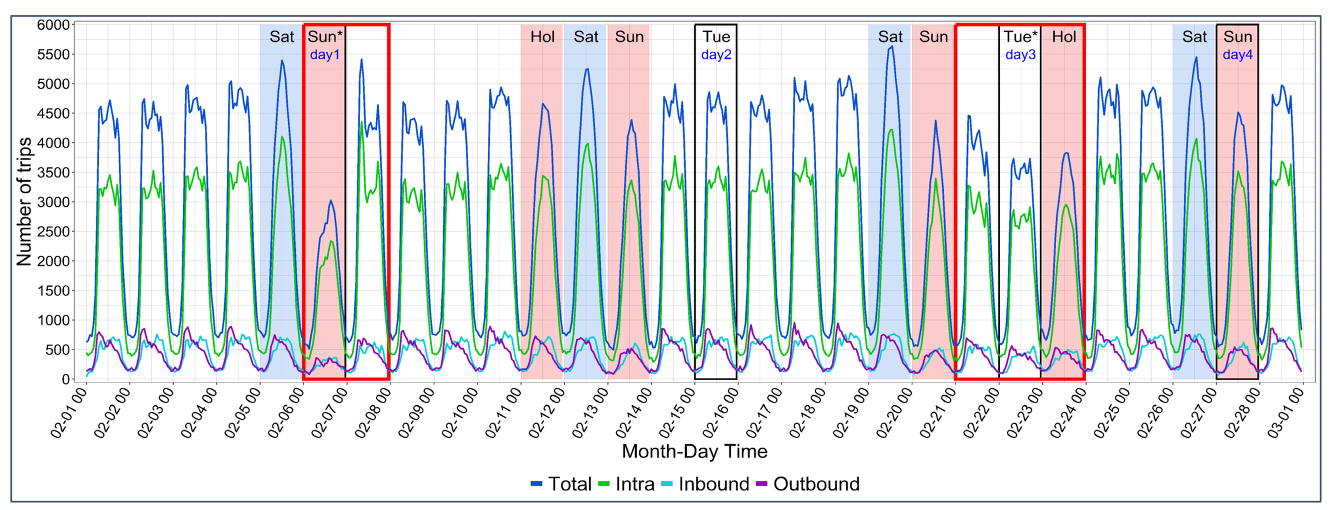
- Revealing effects heavy snowfall on commuting patterns.
- Support disaster prevention and mitigation plans

Data & Method

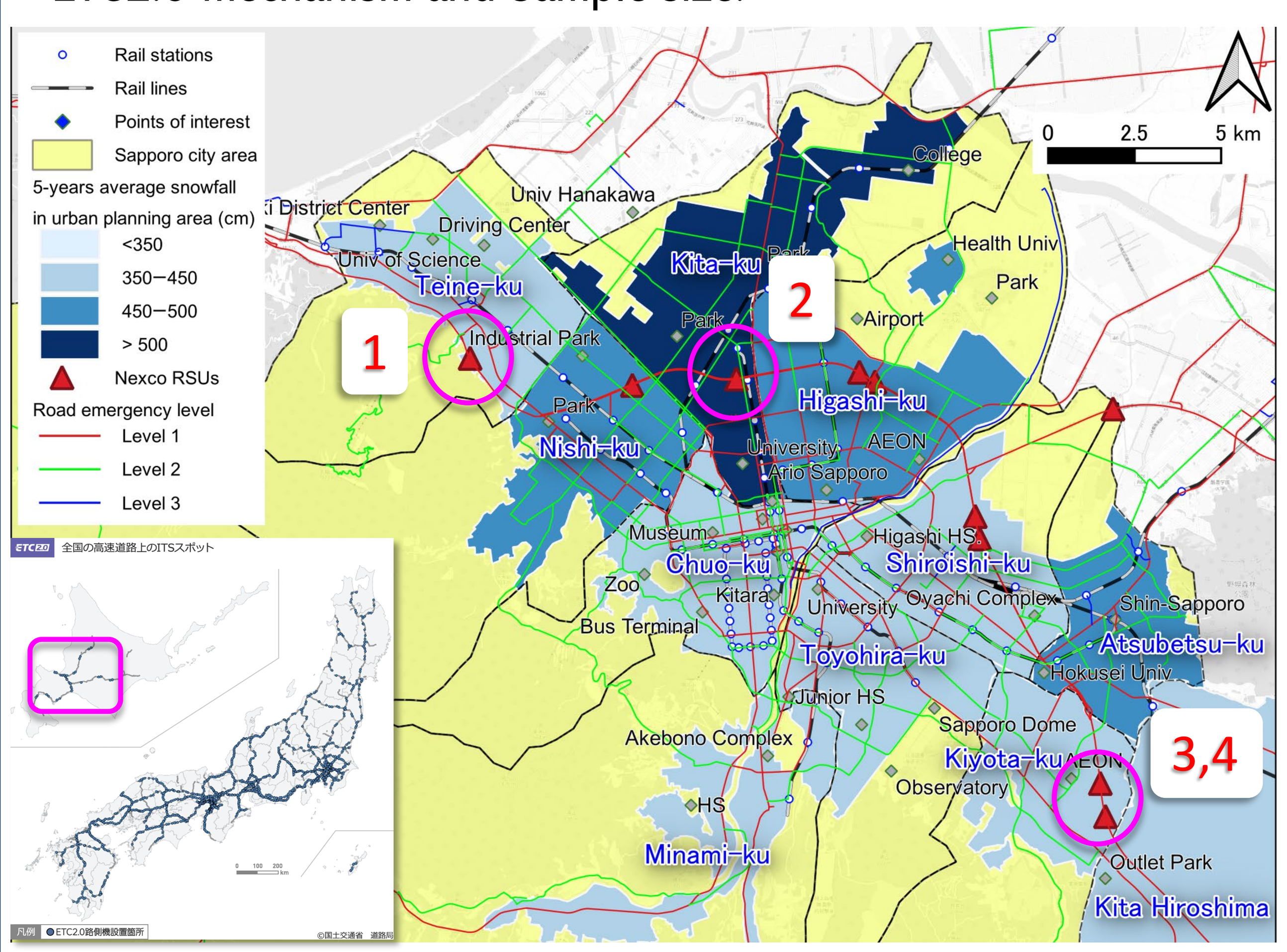




* Selected data and Analysis algorithm



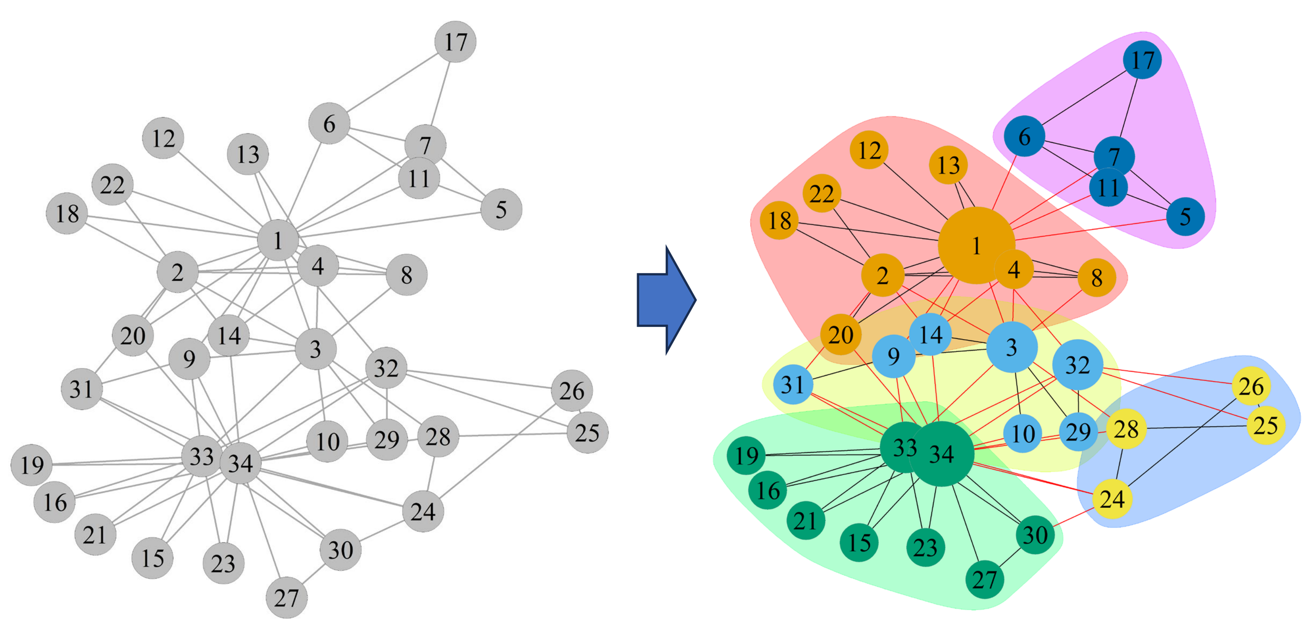
* ETC2.0 mechanism and Sample size.



RSU number	1	2	3	4
Direction (1)	D	D	U	D
Detected vol (2)	1,232	2,067	2,872	2,850
Traffic census (2)	7,715	13,533	15,078	16,169
RSU proportion	16.0%	15.3%	19.0%	17.6%

(1) D – Downstream; U – Upstream ; (2) vehicle/day

* Network clustering by Infomap method.



Infomap algorithm

$$L(M) = q_{\curvearrowright} H(\mathcal{Q}) + \sum_{i=1}^{m} p_{\circlearrowright}^{i} H(\mathcal{P}^{i}) \quad (1)$$

$$q_{\curvearrowright} = \sum_{i=1}^{m} q_{i\curvearrowright} \quad (2)$$

$$p_{\circlearrowright}^{i} = \sum_{\alpha \in i} p_{\alpha} + q_{i\curvearrowright} \quad (3)$$

$$H(\mathcal{Q}) = -\sum_{i=1}^{m} \frac{q_{i\curvearrowright}}{q_{\curvearrowright}} log\left(\frac{q_{i\curvearrowright}}{q_{\curvearrowright}}\right) \quad (4)$$

$$H(\mathcal{P}^{i}) = -\sum_{\alpha \in i} \frac{p_{\alpha}}{p_{\circlearrowright}^{i}} log\left(\frac{q_{\alpha}}{p_{\circlearrowright}^{i}}\right) - \frac{q_{i\curvearrowright}}{p_{\circlearrowright}^{i}} log\left(\frac{q_{i\curvearrowright}}{p_{\circlearrowright}^{i}}\right) \quad (5)$$

** Network modularity*

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i^{out} k_j^{in}}{2m} \right] \delta(c_i, c_j) \quad (6)$$

** Adjusted Rand index*

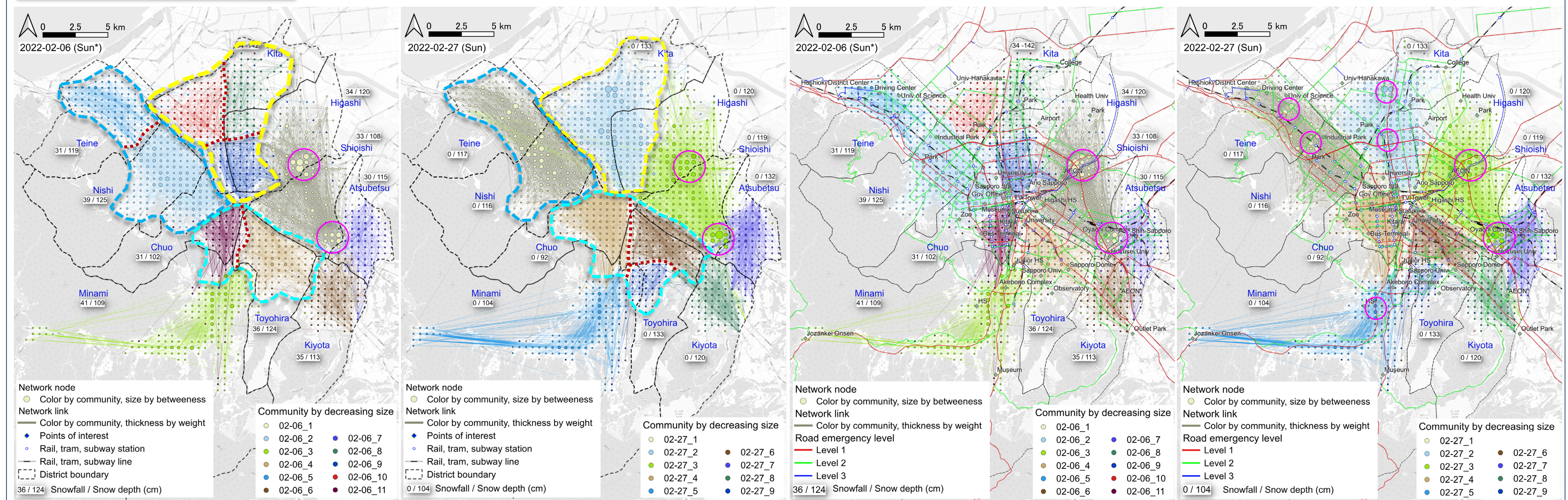
$$ARI = \frac{RI - Expected_{RI}}{\max(RI) - Expected_{RI}} \quad (7)$$

$$RI = \frac{a + d}{\frac{n(n+1)}{2}} \quad (8)$$

** Node betweenness centrality*

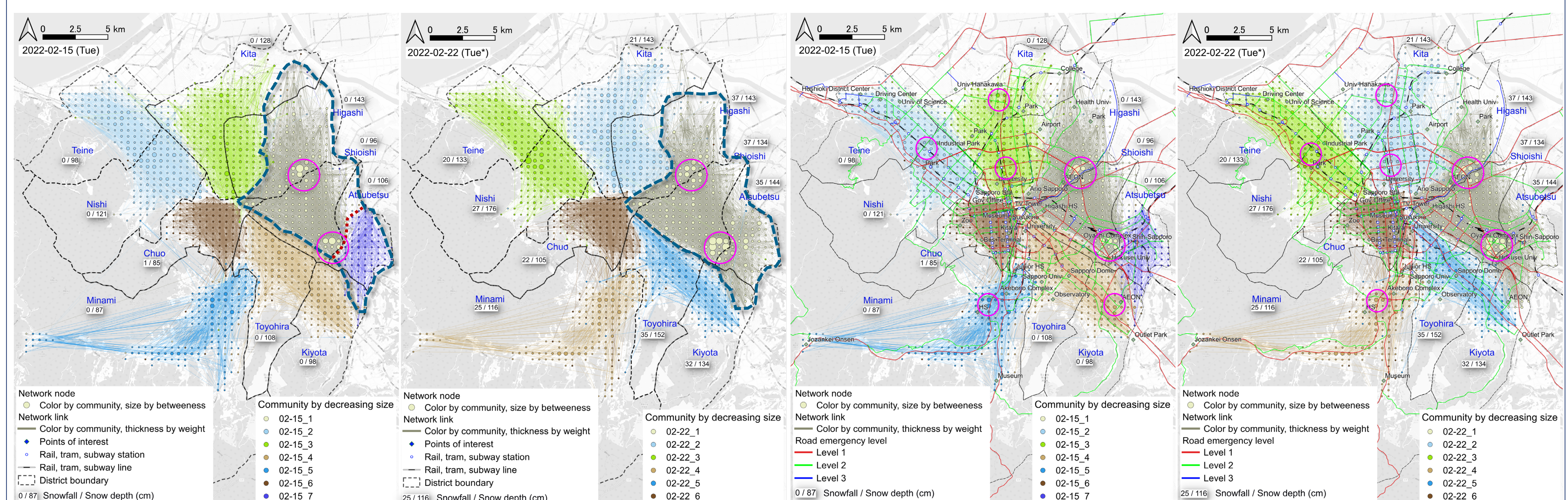
$$Cb(v) = \sum_{s \neq t \neq v} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (9)$$

Results



	day1 (Sun*)	day2 (Tue)	day3 (Tue*)	day4 (Sun)
day1 (Sun*)	0.45	0.44	0.37	0.45
day2 (Tue)		0.40	0.57	0.57
day3 (Tue*)			0.40	0.50
day4 (Sun)				0.44

- Modularity values indicate that the network structures are significant.
- ARI values suggest a medium agreement between networks.
- Networks for Sunday (first hit) were more dissimilar than those for Tuesday (second hit).



- Networks are clustered into communities.
- Commuting communities extend beyond the administrative boundaries.
- High betweenness locations are industrial and commercial areas (Aeon malls, Oyachi, etc.,)
- Networks are more fragmented on heavy snow days compared to normal days and on weekends compared to weekdays.
- Some areas, where emergency roads are poorly connected, tend to be fragmented.

Conclusions

- Adverse weather tends to fragment commuting networks. The preceding event may have a higher impact than the latter, possibly due to increased disaster awareness.
- Commuting communities do not align with administrative boundaries, suggesting a relationship between home and work locations, partly reflecting the land-use plan.
- Industrial and commercial areas are key locations that need to maintain connectivity with other areas.
- An emergency road network at the community level should be implemented to enhance connectivity, thereby increasing the city's capacity for disaster prevention and mitigation.