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Enhancing Emergency Medical Services through Spatiotemporal Demand Forecasting and Resource Optimization: A Deep Learning Approach

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Background

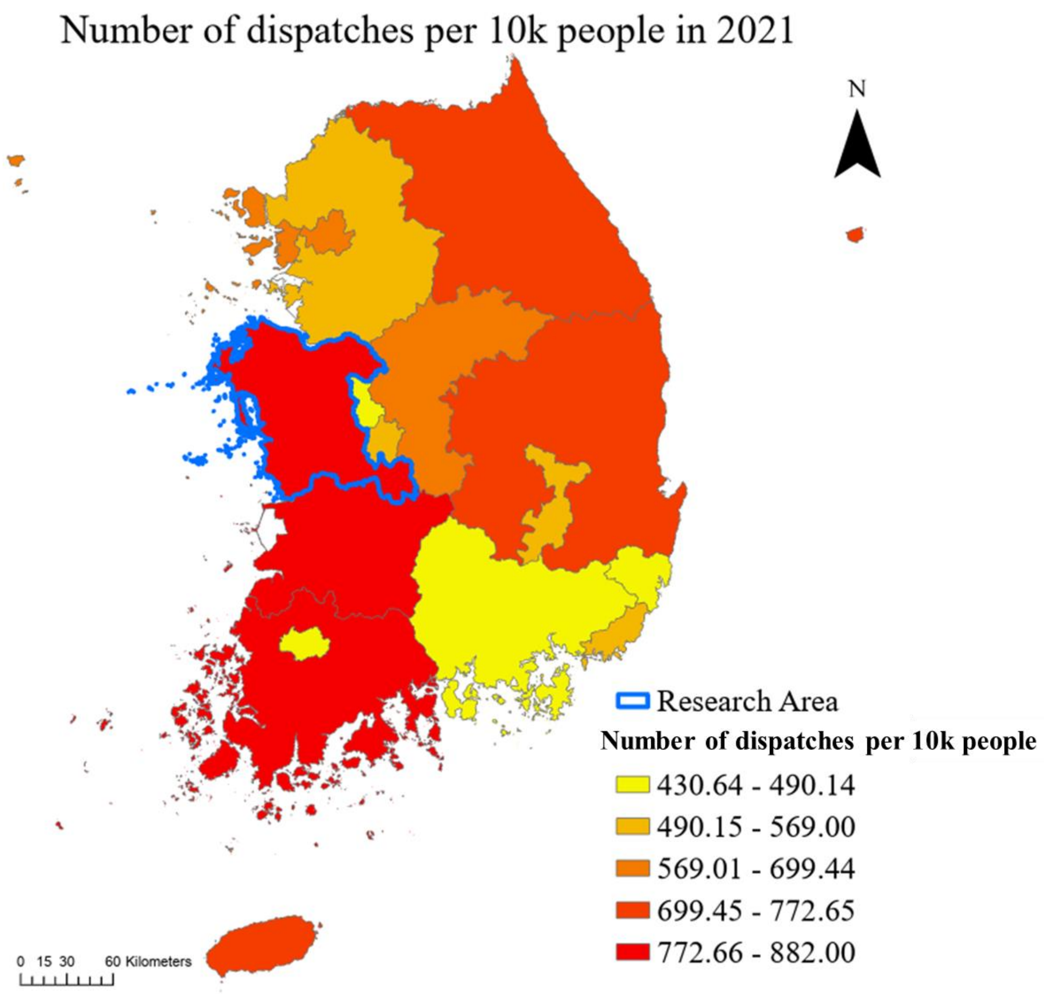
Emergency Medical Services

- Access to ***Emergency Medical Services (EMS)*** is a fundamental right for all individuals (Krafft et al., 2003).
  - EMS is crucial in ***providing rapid medical assistance*** to save lives, especially in emergencies (Cho & Kim, 2020).
  - ***Promptness of emergency care and the availability of emergency medical facilities*** significantly impact patient survival rates (Cho & Kim, 2020).
- Healthcare ***Access Disparity in South Korea***:
  - South Korea faces significant ***healthcare access and utilization disparities*** due to the concentration of medical institutions and professionals in densely populated areas.
  - Despite efforts to address the imbalance in emergency medical services, ***disparities persist, particularly in non-metropolitan areas*** (Cho & Kim, 2020; Kang et al., 2020).

Background

Disparity in South Korea

Figure 1 Number of Ambulance Dispatches in 2021



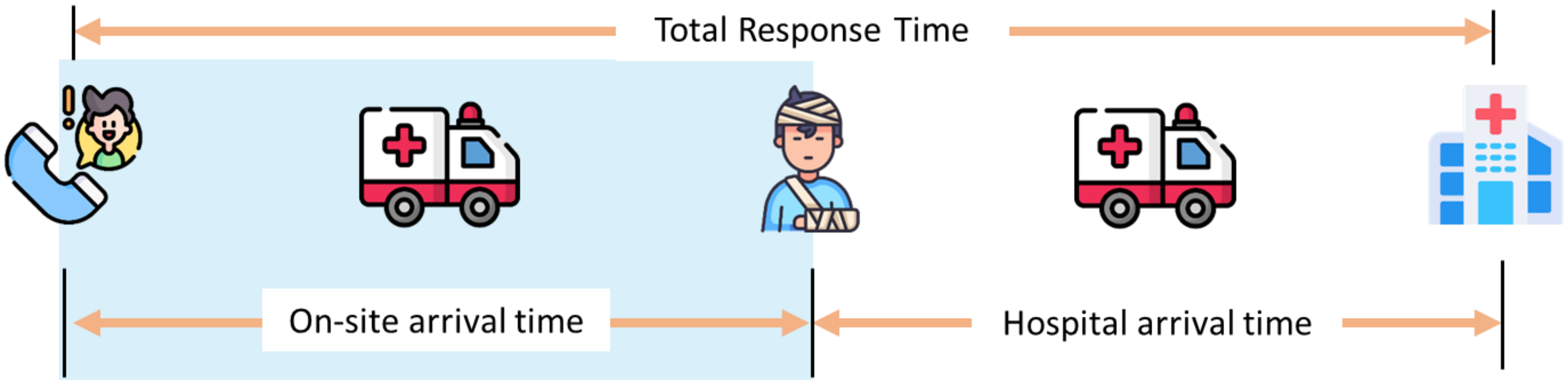
- Approximately ***25% of all hospitals in Korea are located in the capital***, Seoul, and its surrounding areas.
  - Chungcheongnam-do's demand for emergency medical services per 10,000 people ranks third.
  - The emergency medical service response time is approximately 44.3 minutes, the third highest in the country (Korea National Fire Agency, 2022).
- In ***Chungcheongnam-do***, there is a considerable ***population density difference between urban and rural areas***.
  - Living environments, types of industries, and infrastructure are different.
  - There are significant differences in accident types and locations by region (Kim et al., 2021).
- It is necessary to understand ***complex demand patterns*** and ***identify vulnerable areas*** (Cho & Kim, 2020).

Background

Research on EMS Vulnerable Areas

1) Response Time

- EMS response time is a vital metric for assessing the overall quality of healthcare services in an area (Shen et al., 2021).
- Identifying areas for improvement within the emergency medical system (Aboueljinane et al., 2013; Lim et al., 2011; Shen et al., 2021).



Background

Research on EMS Vulnerable Areas

2) Accessibility of Healthcare Services

- It ***evaluates whether the supply of medical services meets the demand within a local community*** (Li et al., 2023).
- ***Even if the supply is similar across areas, differences in ambulance accessibility can arise when demand increases*** (Shen et al., 2021).
- Various accident types and locations can pose unique challenges in each area, necessitating timely and effective emergency care through area-specific approaches (Cho & Kim, 2020).

Various studies have attempted to identify and address EMS weak areas focusing on these two approaches.

Background

Research Related to EMS Vulnerable Areas

EMS demand forecasting using machine learning

- It focused on utilizing machine learning models to predict future demand in various areas (Grekousis & Liu, 2019; Olave-Rojas & Nickel, 2021; Ramgopal et al., 2021).

Measurement of EMS demand patterns using big data

- It measured spatial patterns using spatial data (Rathore et al., 2022; Wang et al., 2023).

EMS resource optimization

- They focus on efficiently allocating emergency medical service resources based on predicted demand (Cho & Kim, 2020; Liu et al., 2021).

- Most studies have utilized ***relatively straightforward prediction models*** for predicting demand patterns.
- Most models ***did not adequately capture the changing patterns over the time*** in predicting EMS demand.

Empirical Strategy

Data and Variables

- **Study Region**: ***16 si-gun-gu within Chungcheongnam-do*** (similar to counties in the United States).

- **Study Period**: Covers the period from ***01/01/2016 to 12/31/2021***.

  - The coordinates of the location of each local fire station were collected based on the street address of the local fire station.

  - **Each case was collected monthly, daily, and hourly**, and ***963,676 cases*** were used in this study.

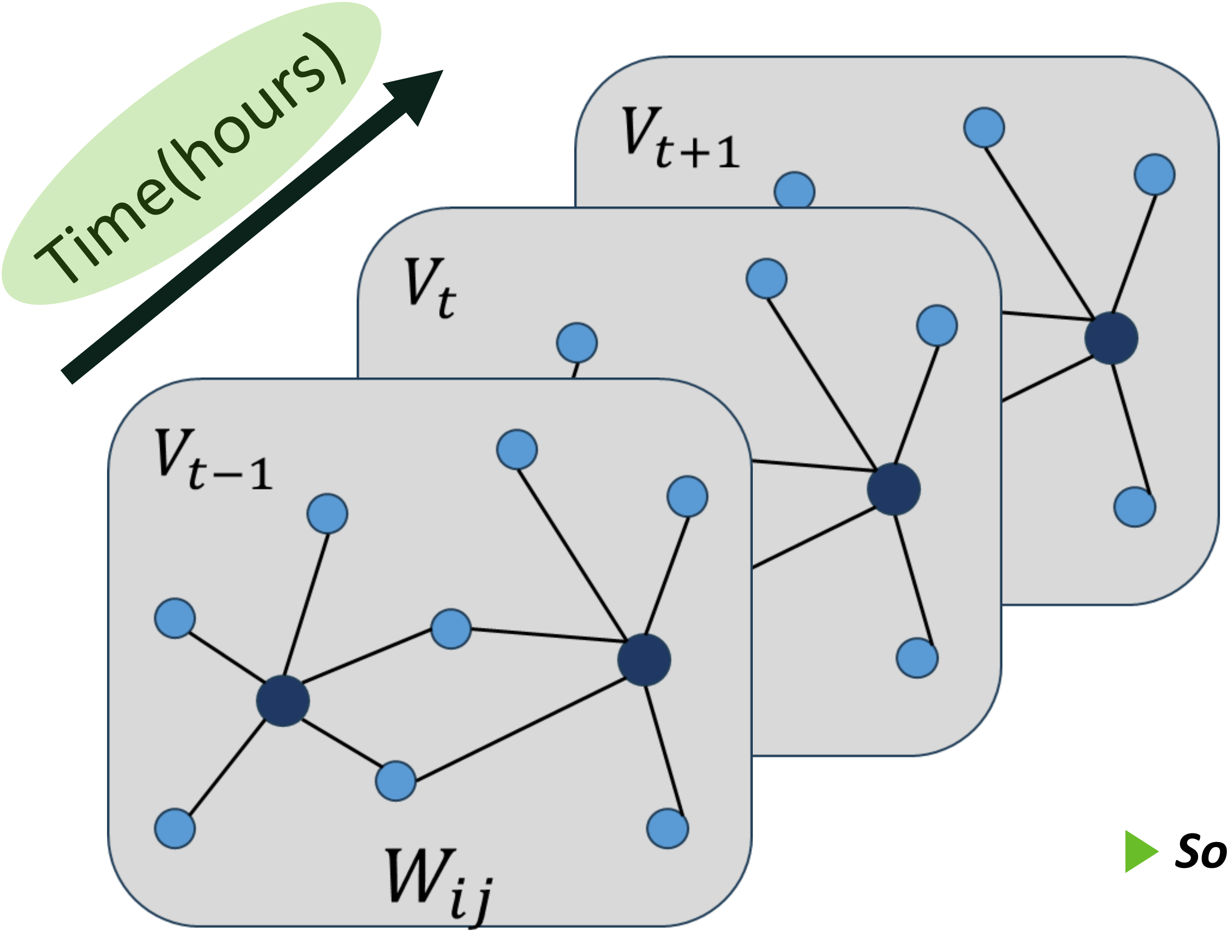
- **Data Sources**:

- EMS Data: Collected from 'Chungcheongnam-do Fire Headquarters.'

- Demographic Data: Obtained from 'Korean Statistical Information Service (KOSIS).'

Empirical Strategy

Spatial-Temporal Graph Convolutional Networks



Step 1. Predicting Demand Patterns

- It reflects ***regional connectivity and heterogeneity***.
- ***Captures change in the time*** of nodes connected to each node.
  - For example, predicting demand patterns that change every hour is possible.
- ***Predict complex EMS demand patterns*** by considering both temporal and spatial location.

- ***So how can we cover such heterogeneous demand patterns with maximum?***

(Yan et al., 2018 ; Jin et al., 2021; Zhao et al., 2023)

Empirical Strategy

Maximum Coverage Location Problem (MCLP)

$$Maximize\ Z = \sum_{i \in I} \sum_{t \in T} a_{it} Y_{it}$$

$$subject\ to\ Y_{it} \leq \sum_{j \in N_i} X_{jt}, \qquad i \in I, t \in T$$

$$\sum_{i \in I} \sum_{t \in T} X_{it} = 95$$

$$0 \leq Y_{it} \leq 1, \quad i \in I, t \in T$$

$$X_{jt} \in \{0, 1\}, \qquad j \in J, t \in T$$

Step 2. Location-Allocation based on predicted demand

- MCLP is a method for calculating ***optimal location*** decisions to ***maximize cover the demand*** (Azizan et al., 2017; Cho & Kim, 2020; Ibarra-Rojas et al., 2020; Ye & Kim, 2016).
- This model can ***identify the changing optimal location with the shifting temporal pattern***.

i: index of a EMS demand grid locations;

j: index of all candidate EMS locations J;

a_{it}: the number of predicted EMS demands present at gird i in period t;

$$x_{jt} = \begin{cases} 1 & if\ site\ j\ is\ selected\ for\ EMS\ in\ period\ t \\ 0 & otherwise \end{cases}$$

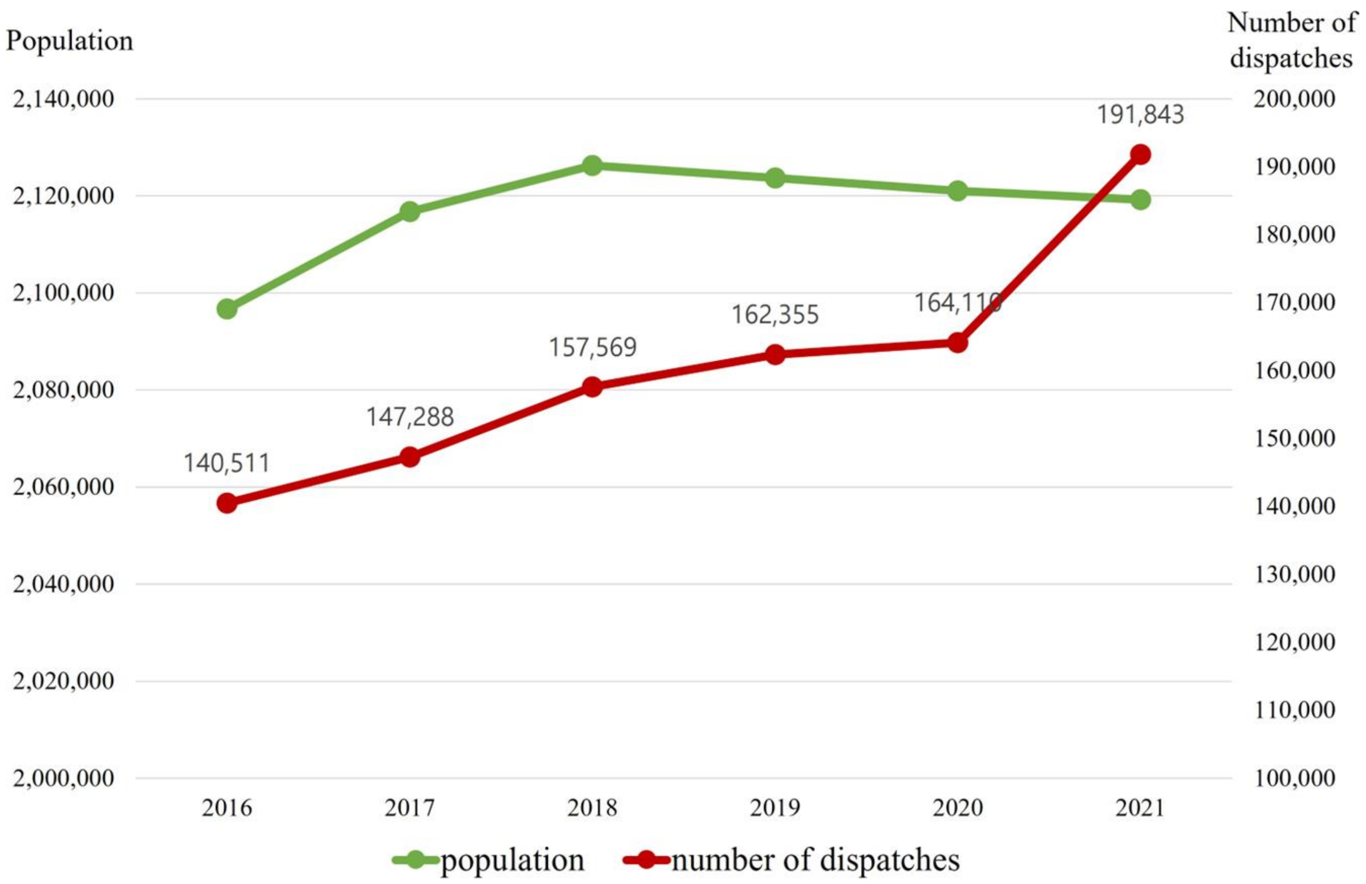
$$Y_{it} = \begin{cases} 1 & if\ demand\ at\ i\ in\ period\ t\ is\ covered\ by\ located\ ambulances \\ 0 & otherwise \end{cases}$$

Azizan et al., 2017; Cho & Kim, 2020

Empirical Strategy

Data and Variables

Figure 2 Chungcheongnam-do population and dispatch trends by year



- The ***total population*** in Chungcheongnam-do is gradually ***decreasing***.
- However, the ***number of EMS dispatch continues to increase***.

Service Demand Side

Emergency medical service demand side

Table 3-1 Chungcheongnam-do population status.

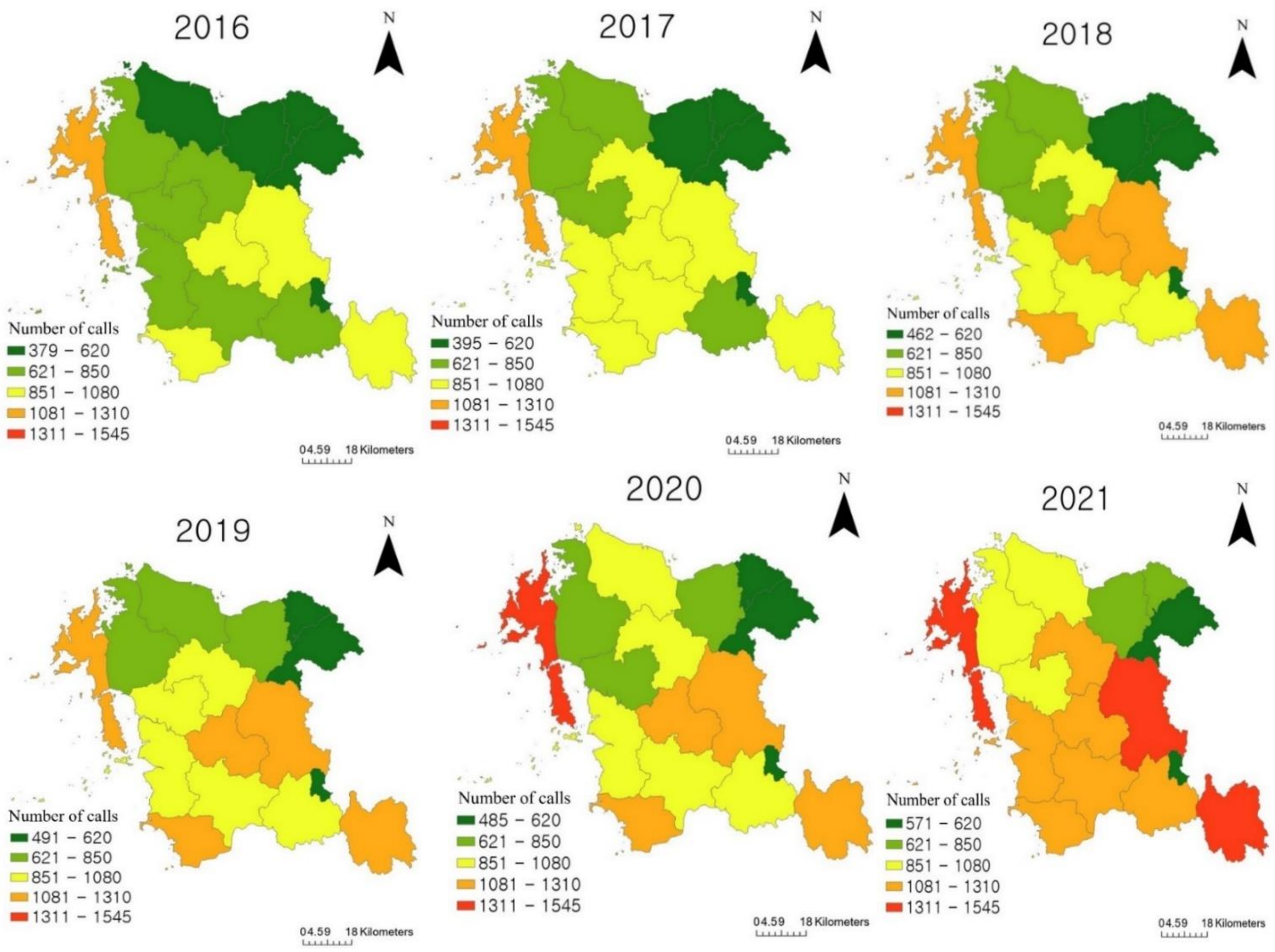
	2016	2017	2018	2019	2020	2021
total population	2,096,727	2,116,770	2,126,282	2,123,709	2,121,029	2,119,257
Gender ratio	103.2	103.4	103.6	103.9	104.3	104.6
Mean age	41.5	41.9	42.3	42.8	43.5	44.1
Elderly ratio	16.7	17.1	17.5	18.2	19.1	19.8
Number of calls	141,484	147,366	157,569	162,334	163,994	191,813
Number of calls per capita	0.067	0.070	0.074	0.076	0.077	0.091

Gender ratio = (total male population/total female population)*100
Elderly population ratio = (Population over 65/Total population)*100
Source: National Statistics Portal

- The overall population of South Chungcheong Province is gradually decreasing.
- The ***average age*** is gradually increasing, and the ***proportion of elderly people*** is also growing.
- At the same time, ***the number of EMS reports is also increasing over time***.

Service Demand Side

Figure 3 Number of emergency medical service call per 10,000 population



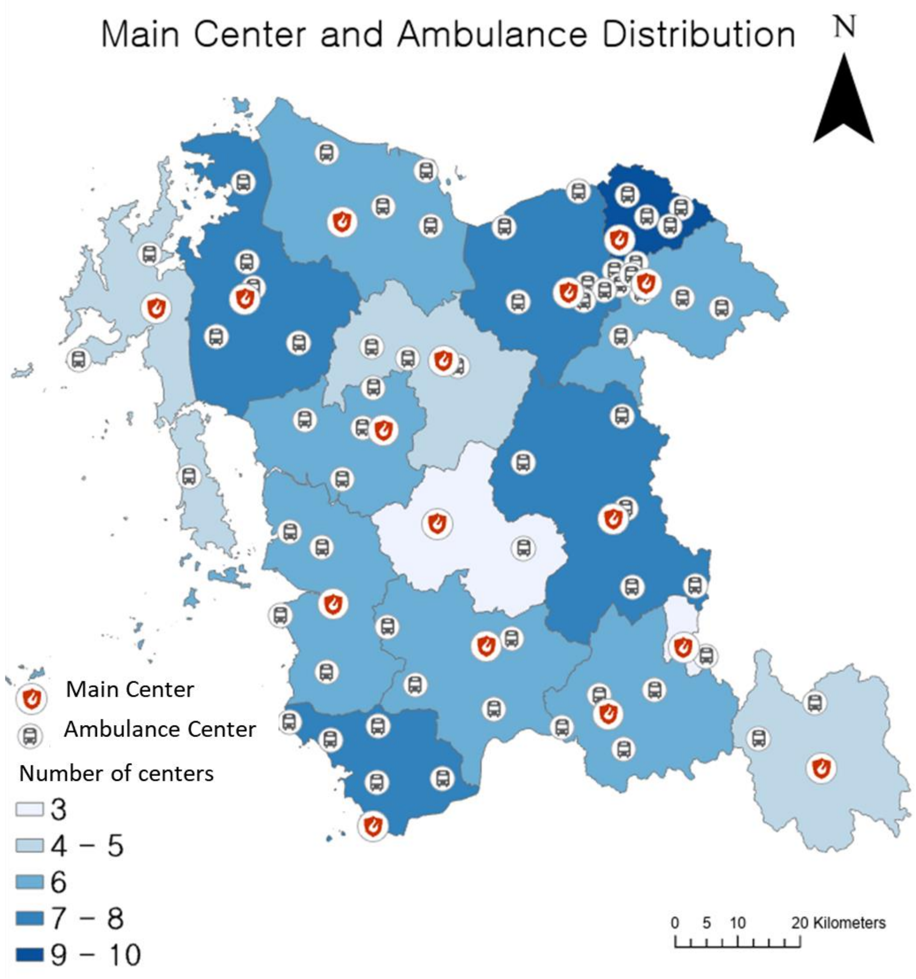
- It is a change in ***demand over time and space***.
  - This is the number of calls per 10,000 people.

- ***Overall demand is increasing over time***.
- There are ***differences in demand by region***, and the gap is gradually ***worsening***.

Service Supply Side

Emergency medical service supply side

Figure 4. Distribution of emergency medical service resources by region

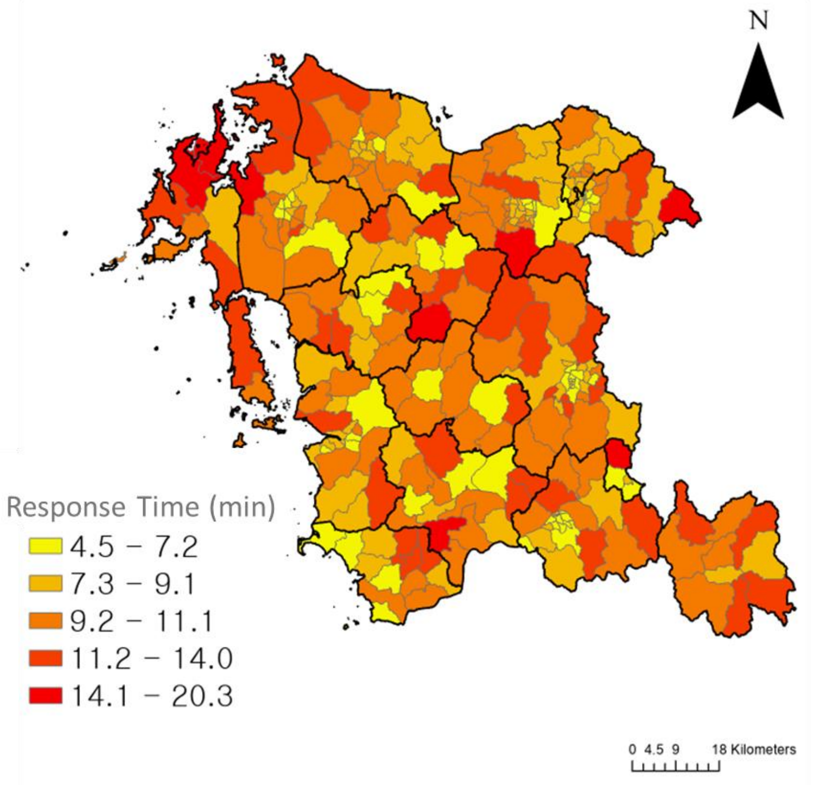


- There are ***95 ambulances*** in operation in the region.
- EMS centers are mainly ***concentrated in urban areas***.
- The overall distribution of centers is relatively evenly distributed.
  - However, spatial uniformity cannot guarantee optimal supply depending on demand patterns.

Service Supply Side

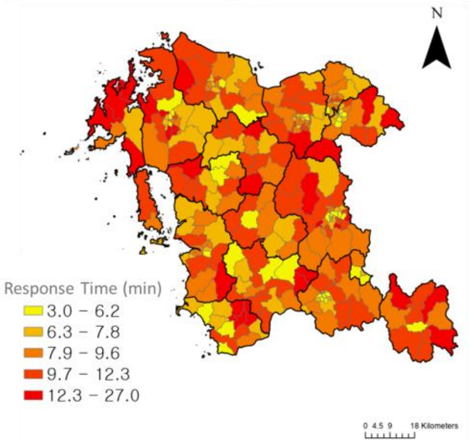
Response time to 119 call location

Total Response Time

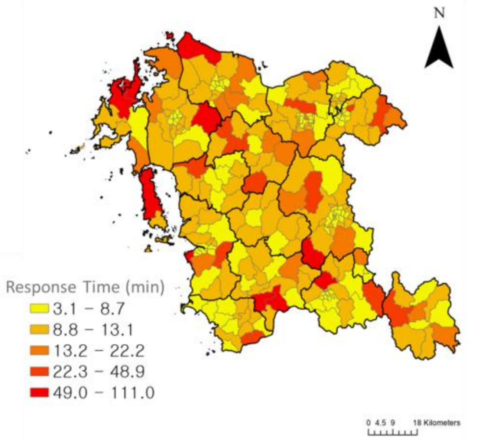


Accident Type

Injury

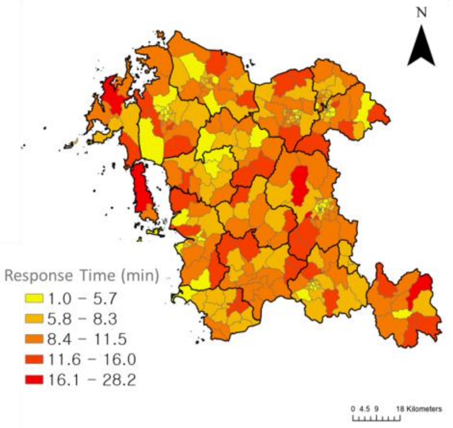


Fire

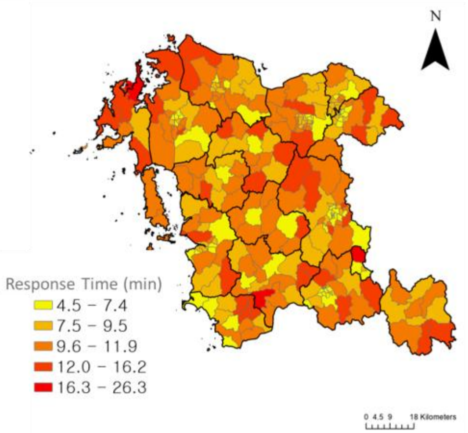


Accident Location

Road



House



Empirical Strategy

Empirical Analysis Model

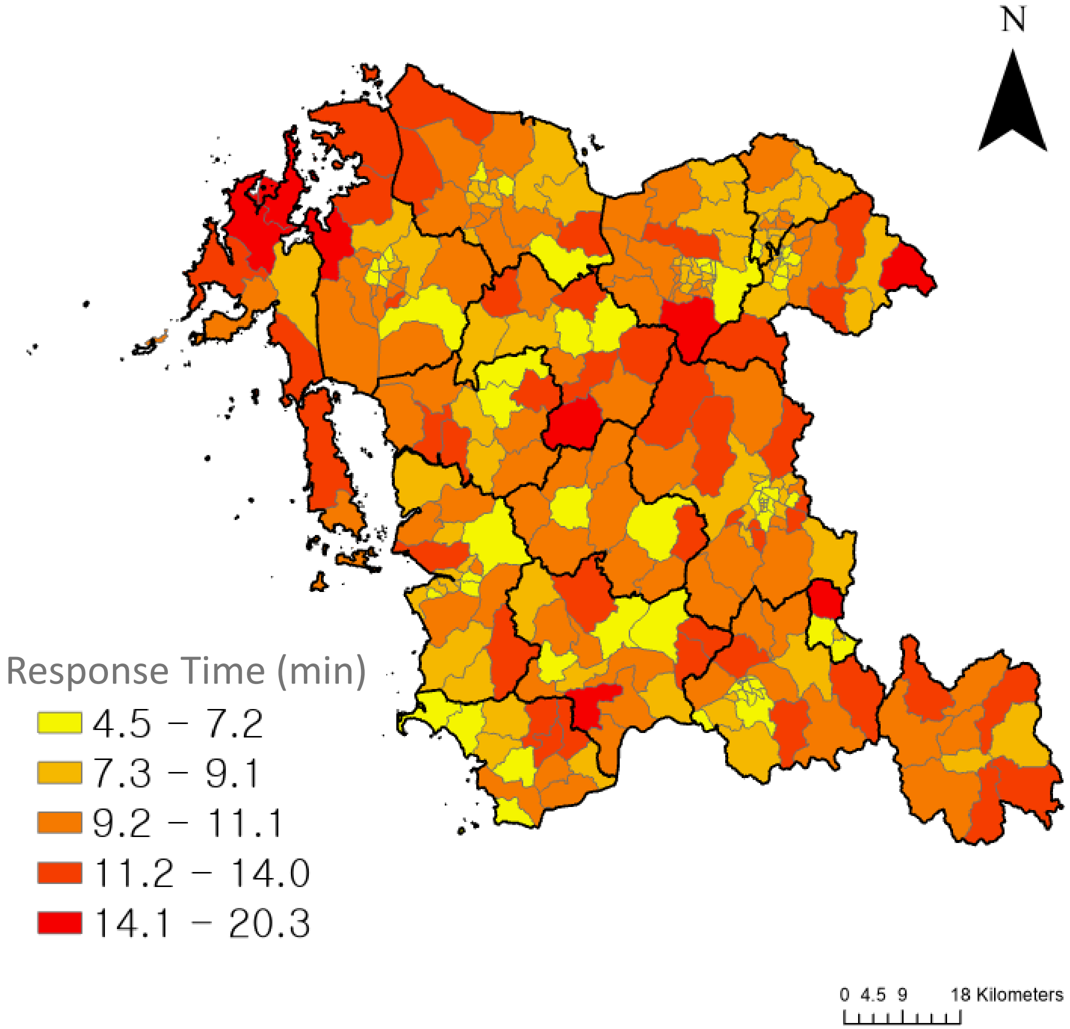
- What the preceding maps and diagrams tell us is that the ***patterns of supply and demand appear differently depending on time, region, location of accident, and type of accident***.
- There are also large differences by region.
  - Considering only the number of EMS reports, ***heterogeneity by time and region*** cannot be reflected.
  - It is ***difficult to predict demand with a simple linear model***.

- ***Prediction results that consider spatial patterns and changes over time are essential.***

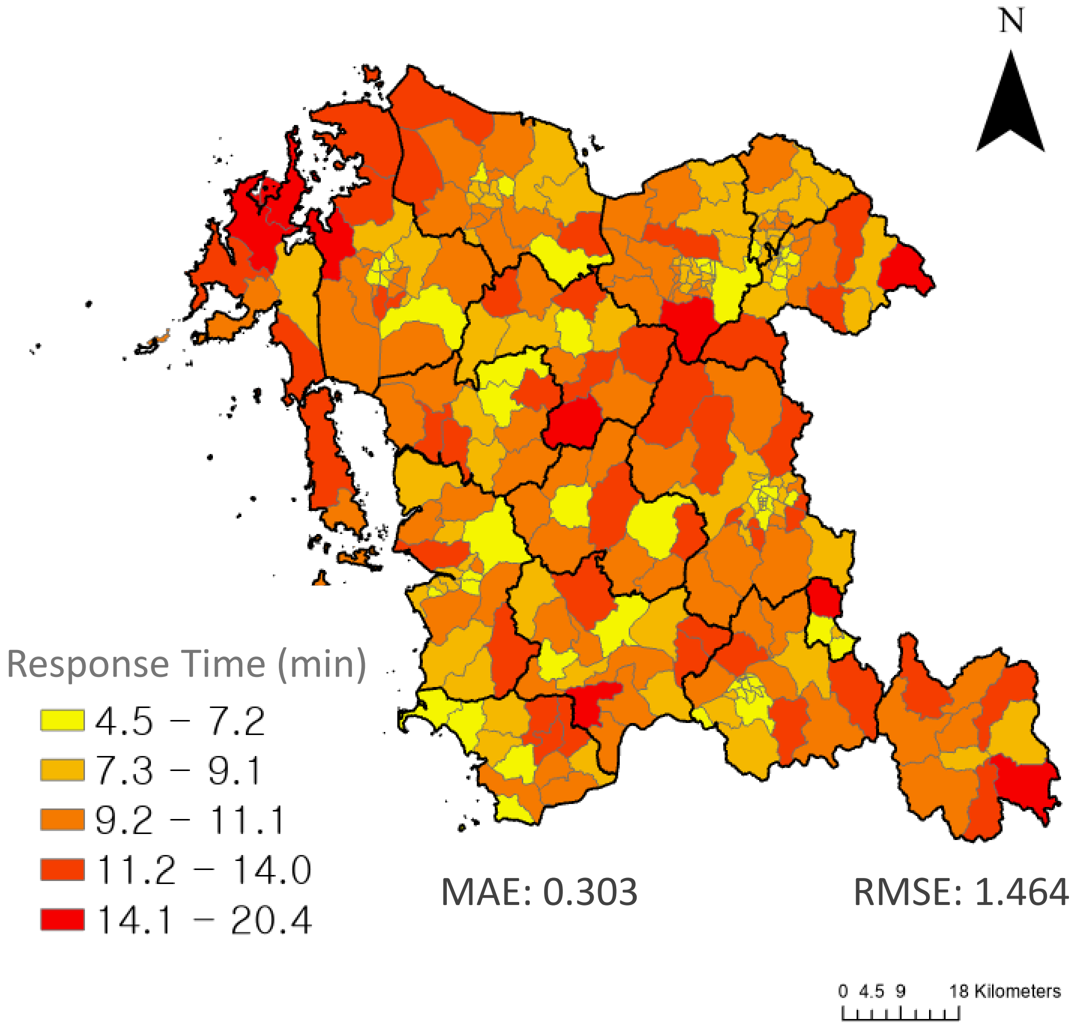
Spatial-Temporal Graph Convolutional Networks

Predicted Results

Observed Response Time



Predicted Response Time



MAE: 0.303

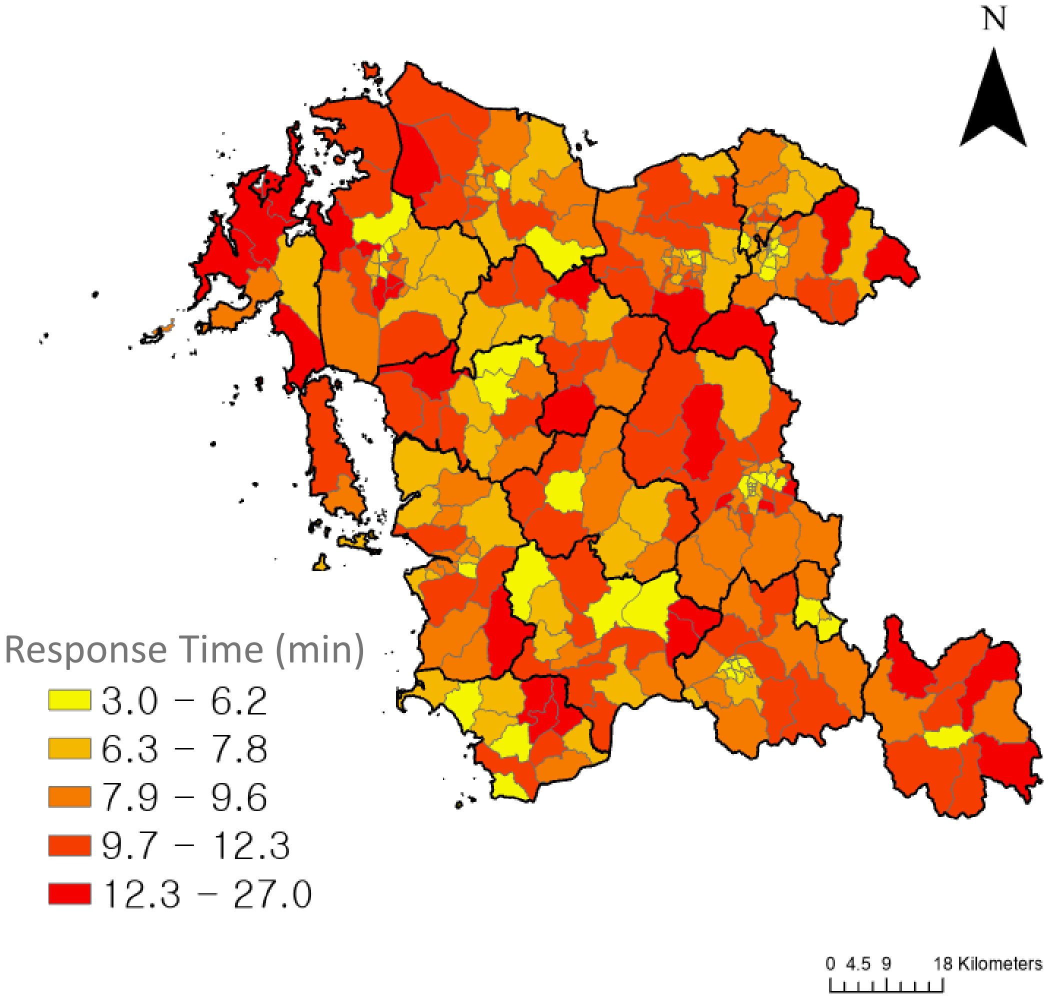
RMSE: 1.464

Spatial-Temporal Graph Convolutional Networks

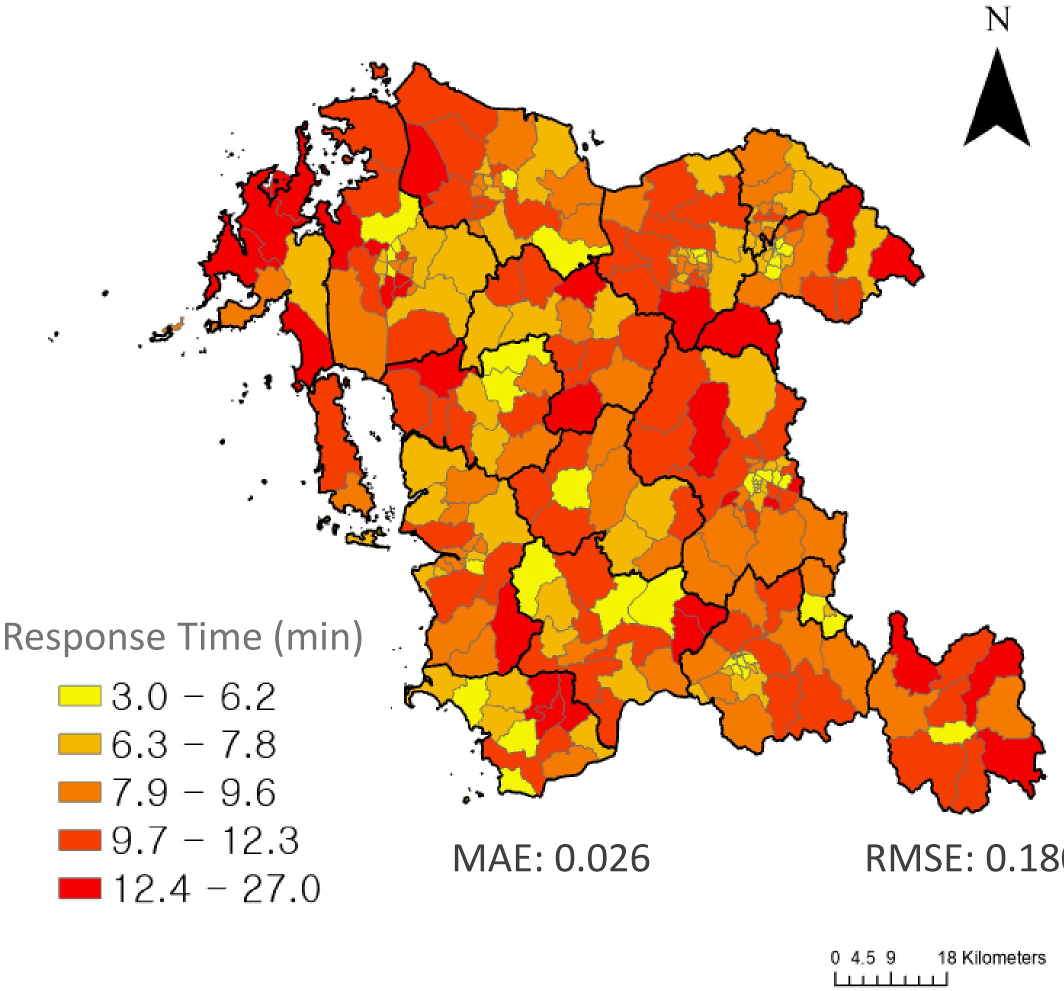
Predicted Results

By Accident Type

Observed Response Time
Injury



Predicted Response Time
Injury



MAE: 0.026

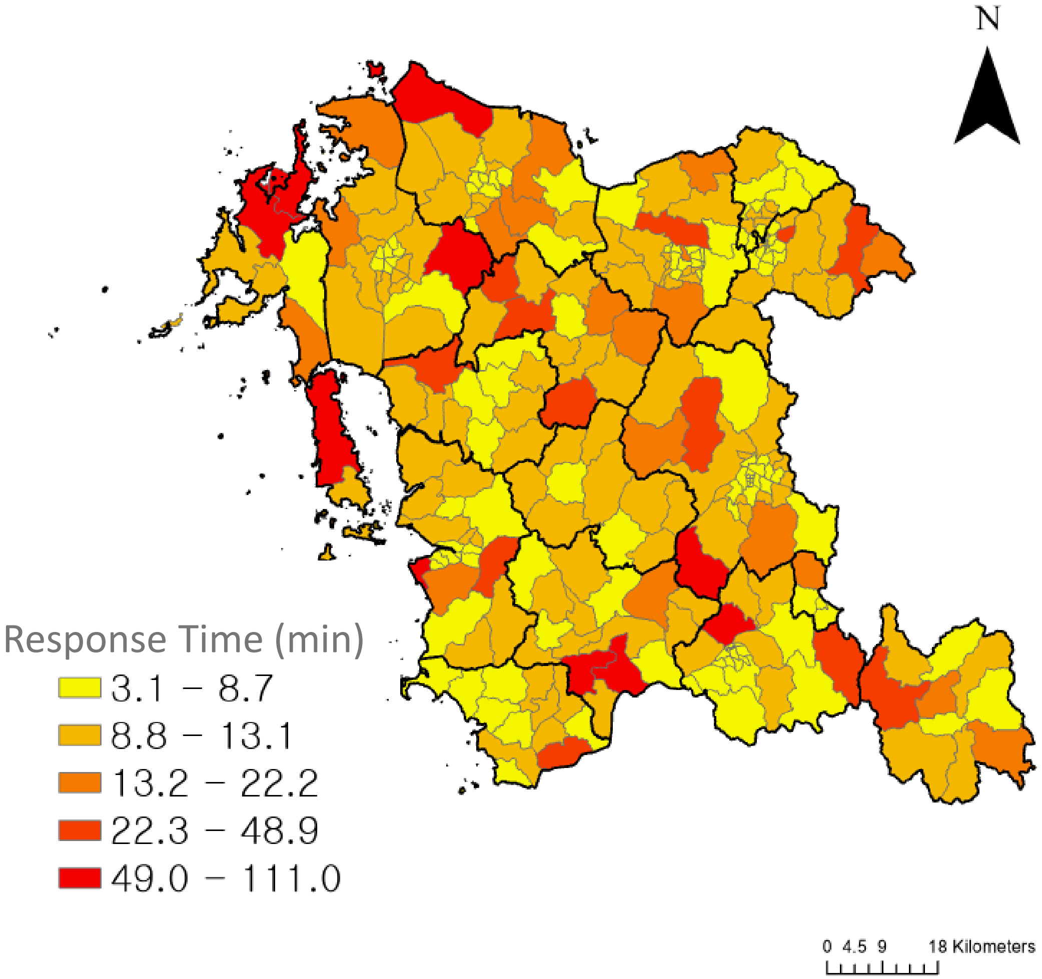
RMSE: 0.180

Spatial-Temporal Graph Convolutional Networks

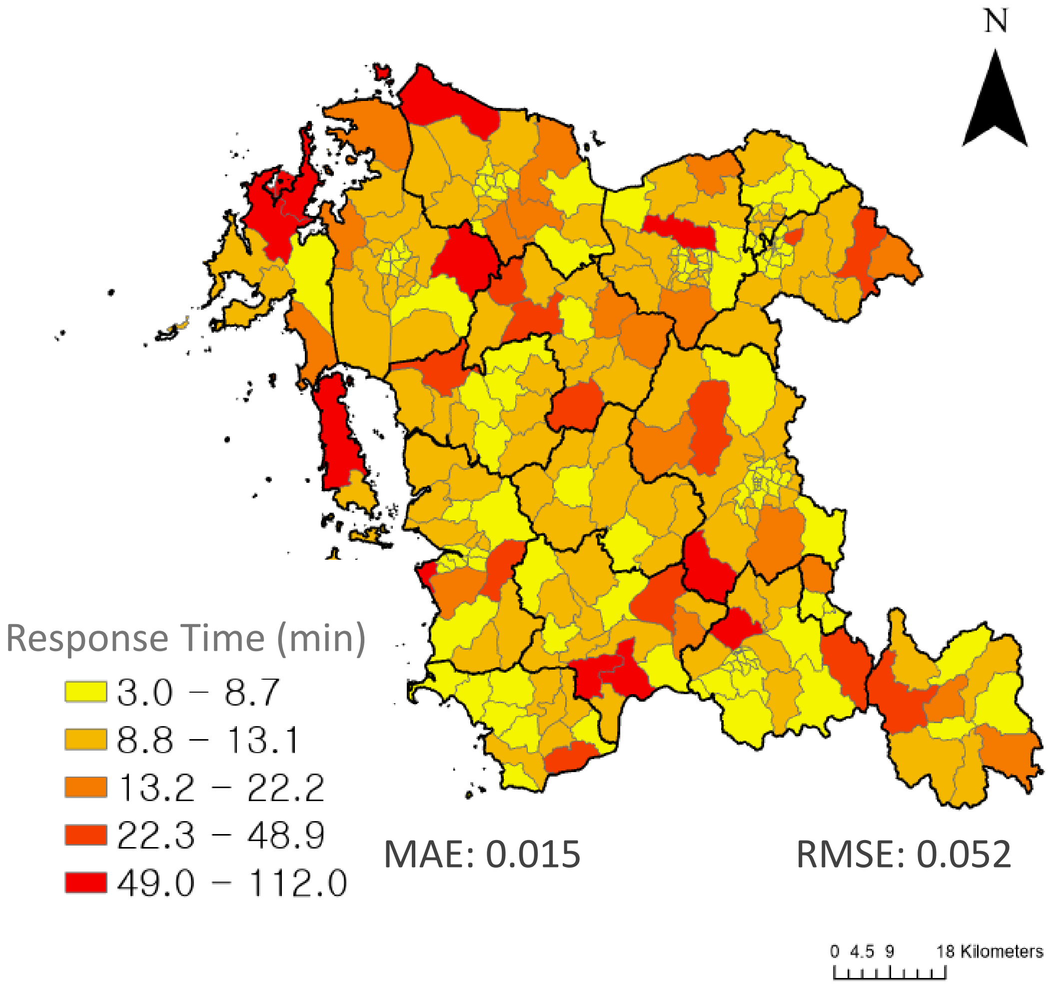
Predicted Results

By Accident Type

Observed Response Time
Fire



Predicted Response Time
Fire



MAE: 0.015

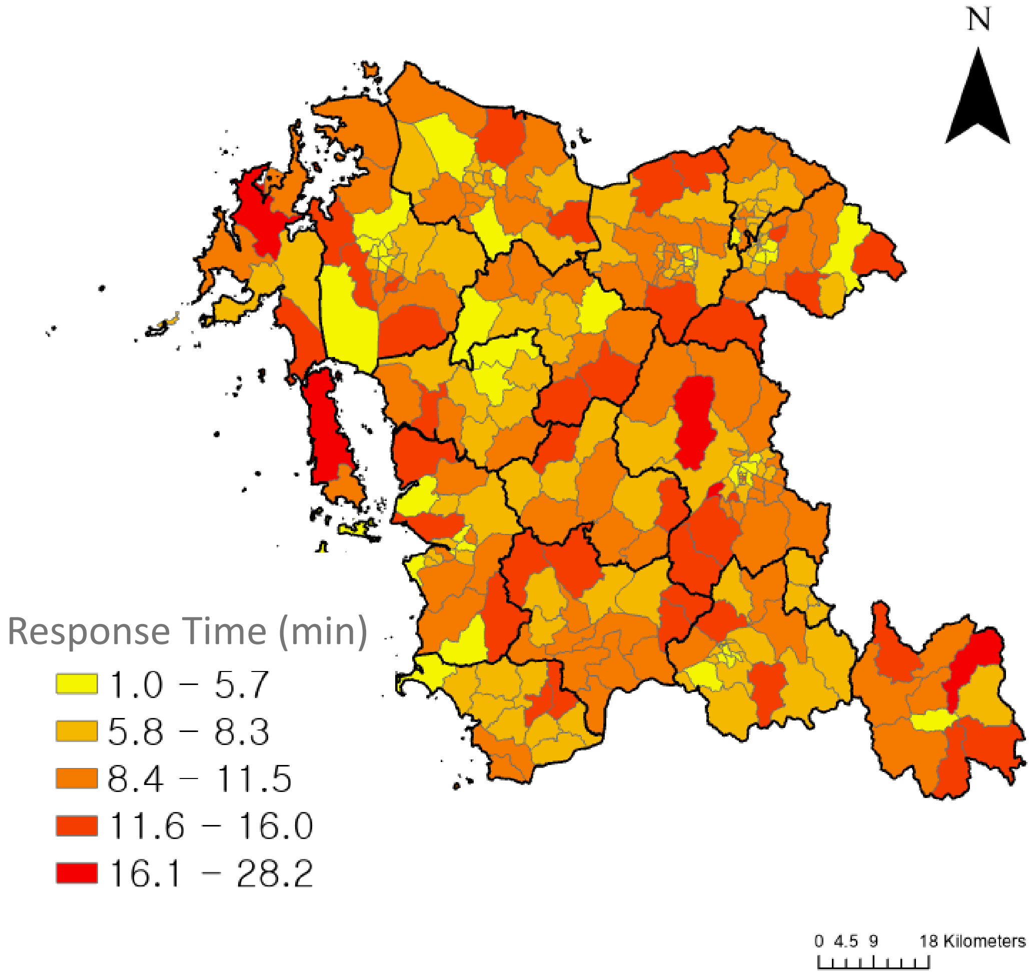
RMSE: 0.052

Spatial-Temporal Graph Convolutional Networks

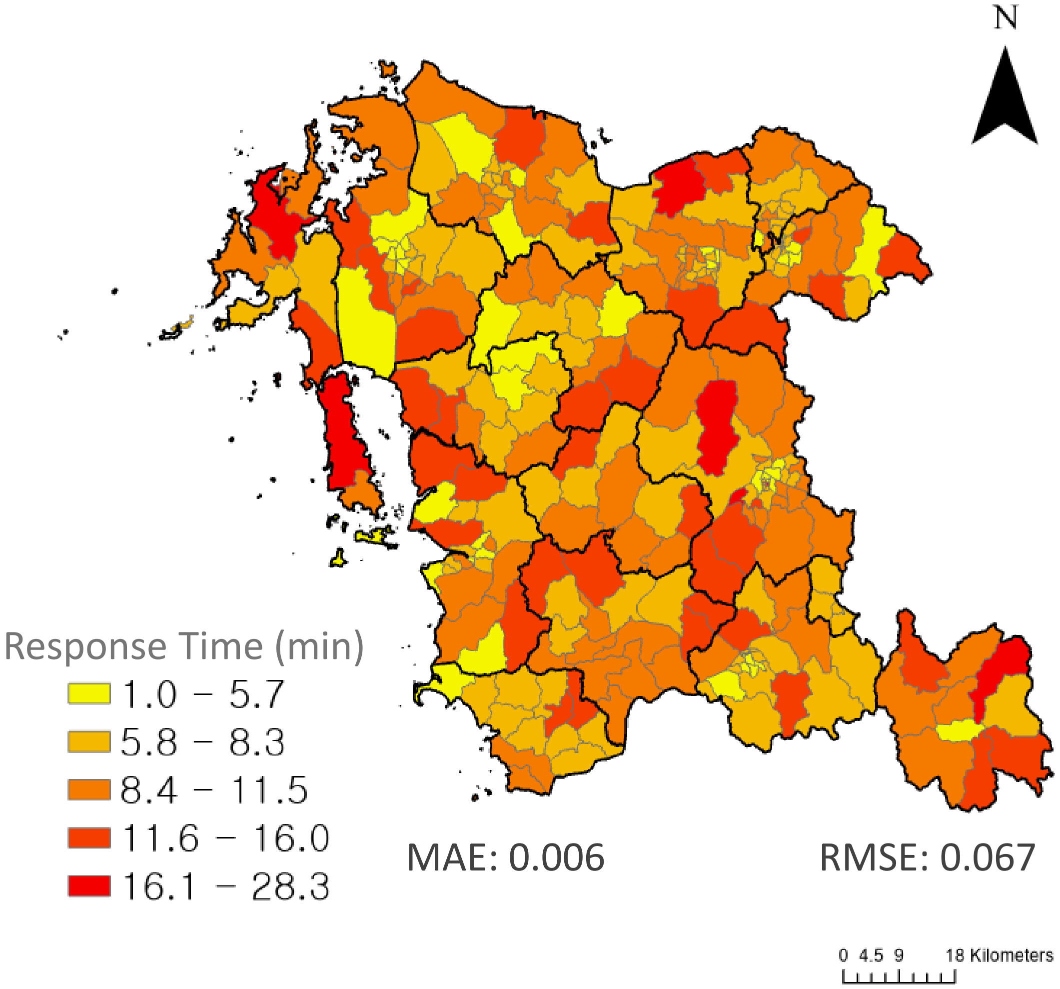
Predicted Results

By Accident Location

Observed Response Time
Road



Predicted Response Time
Road



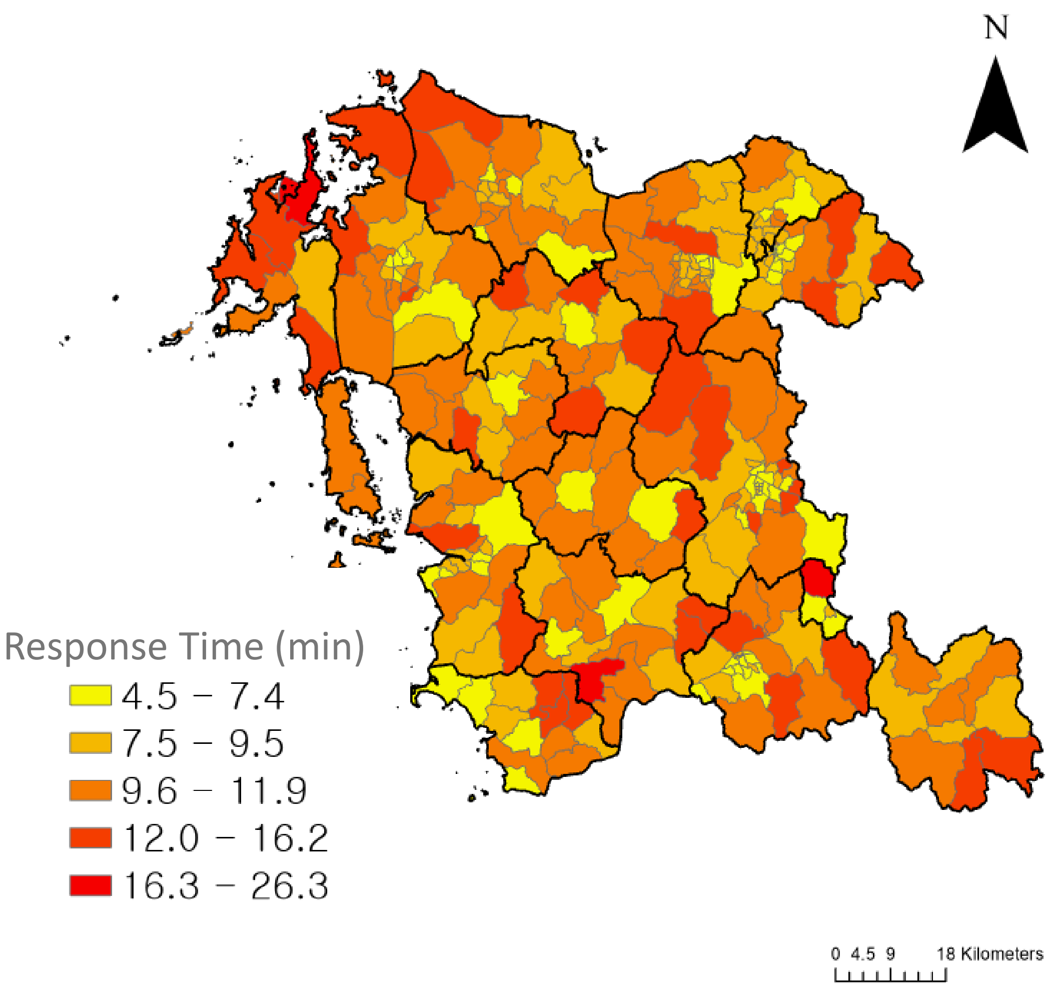
MAE: 0.006 RMSE: 0.067

Spatial-Temporal Graph Convolutional Networks

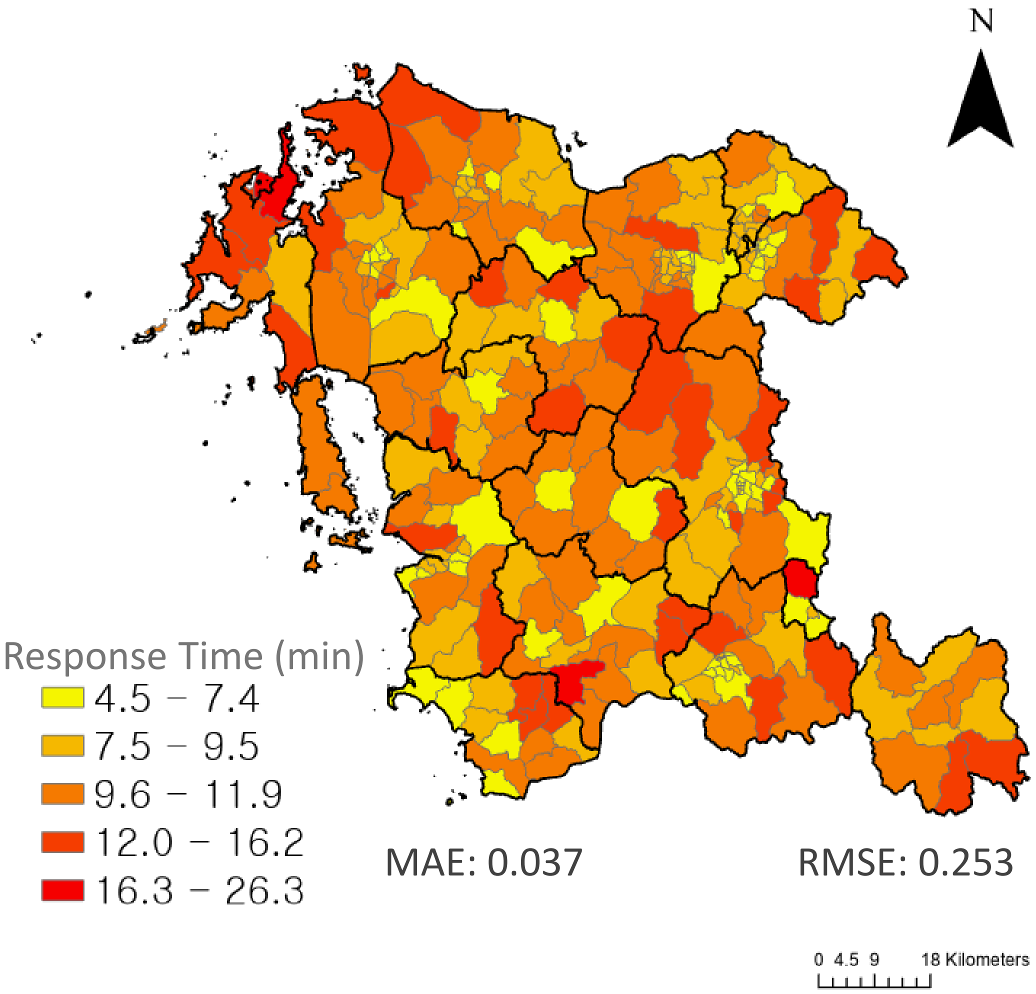
Predicted Results

By Accident Location

Observed Response Time
House



Predicted Response Time
House



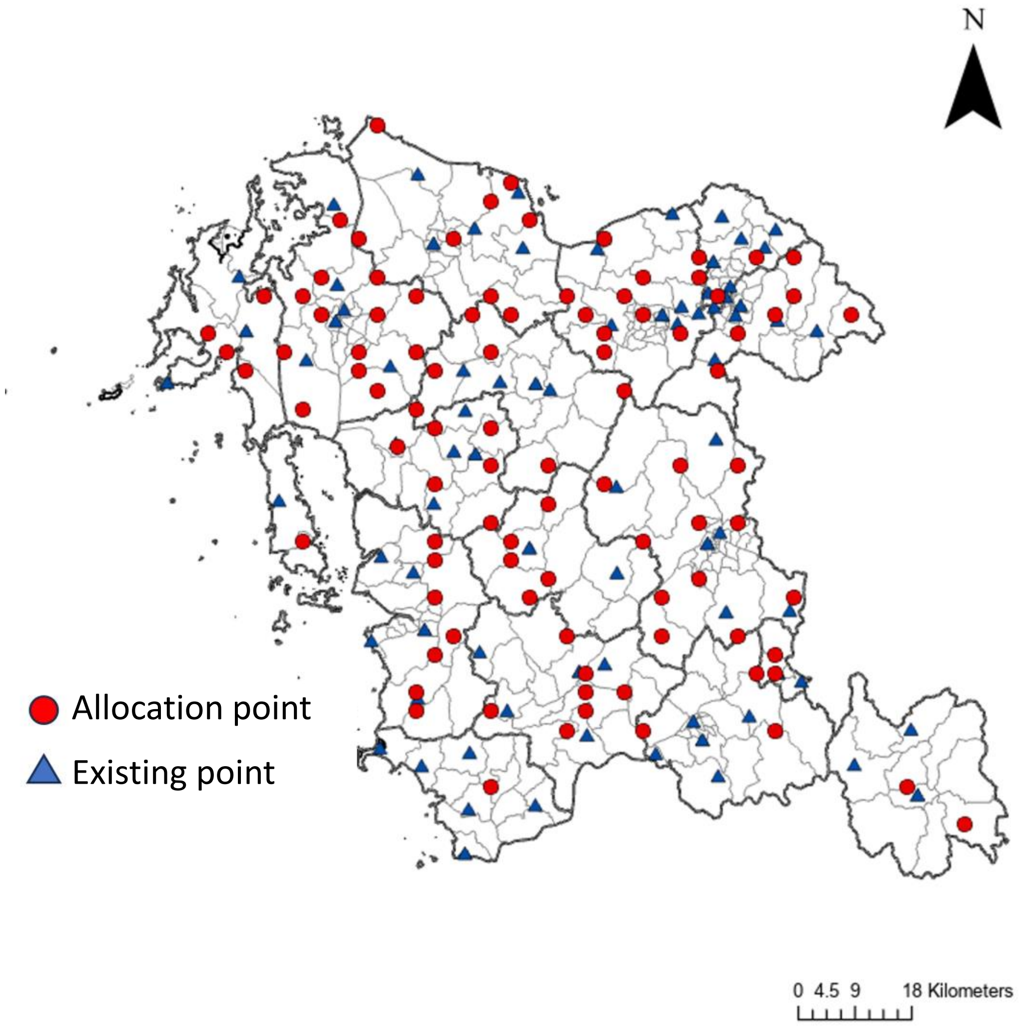
MAE: 0.037

RMSE: 0.253

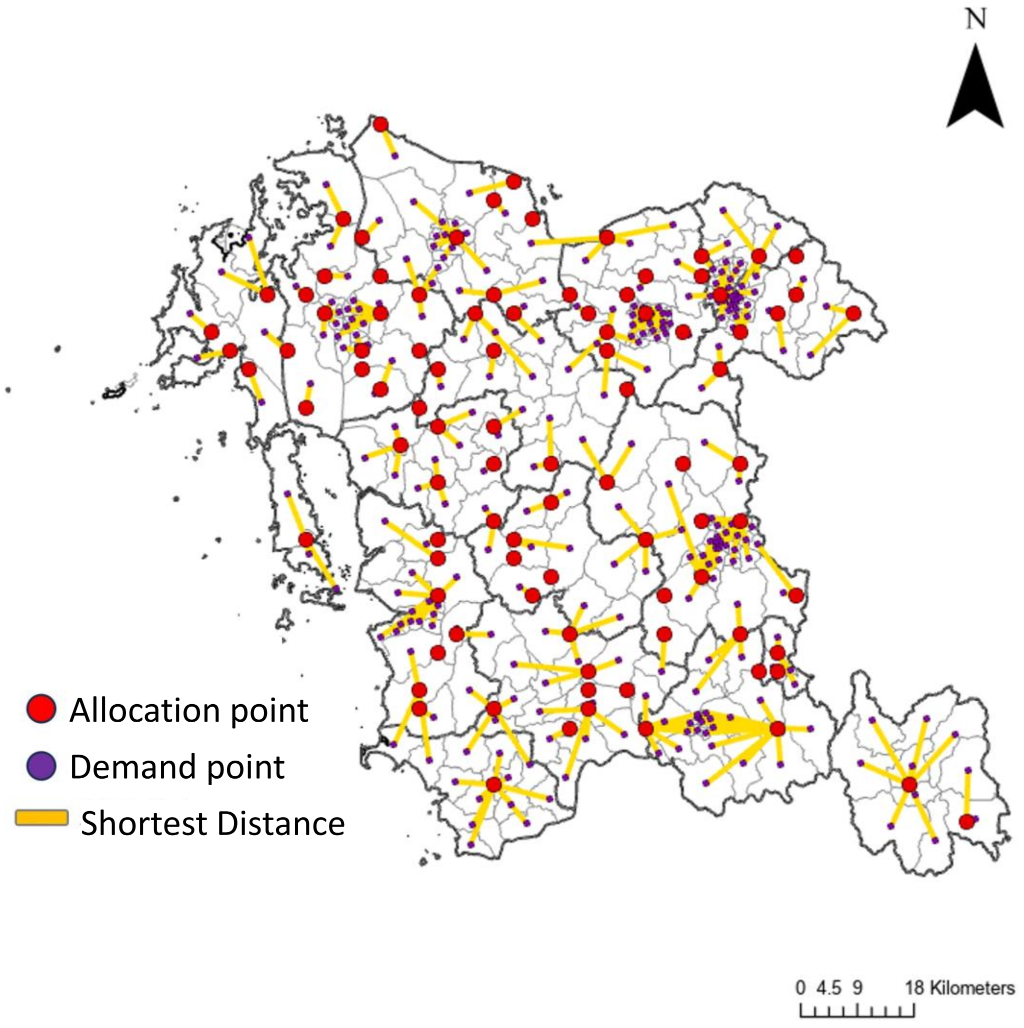
Maximum Coverage Location Problem

Optimization Results

119 Center Location Comparison



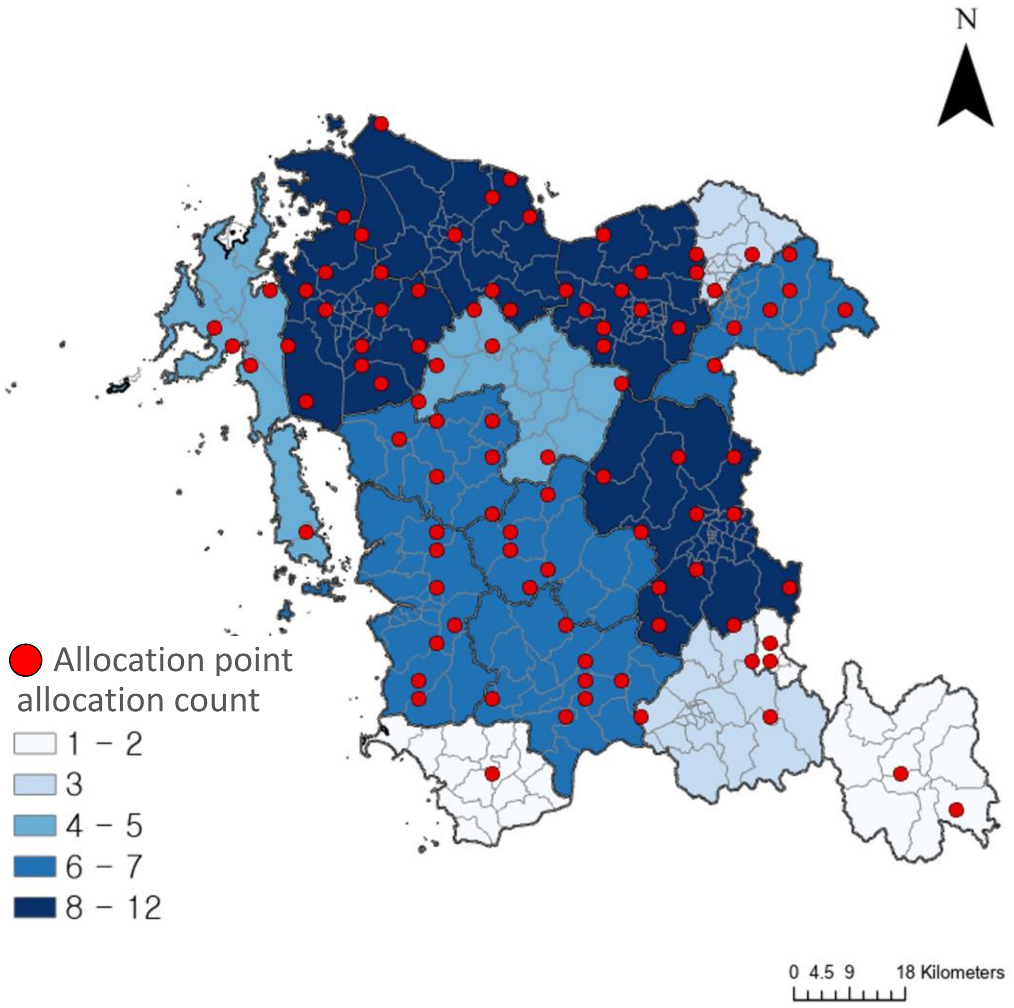
119 Center location allocation



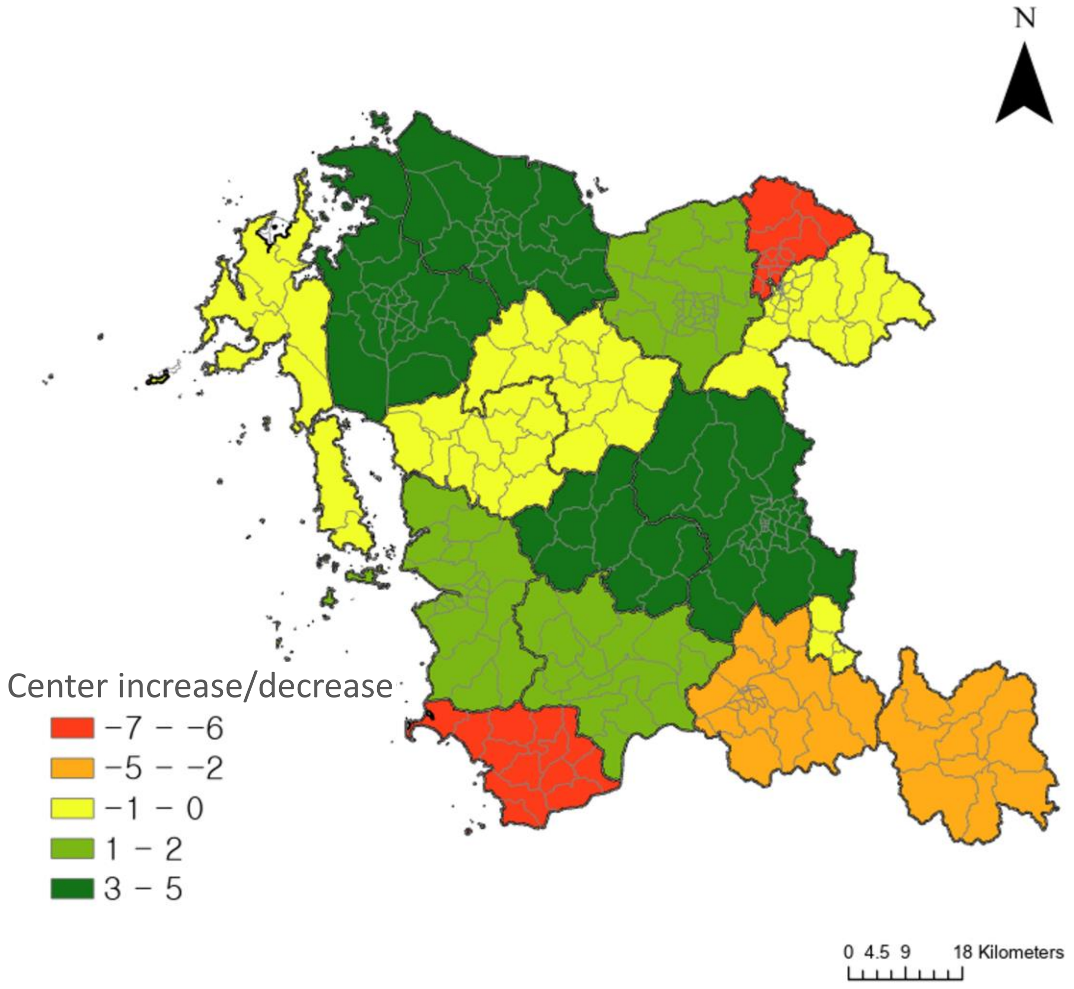
Maximum Coverage Location Problem

Optimization Results

Optimal number of centers per region



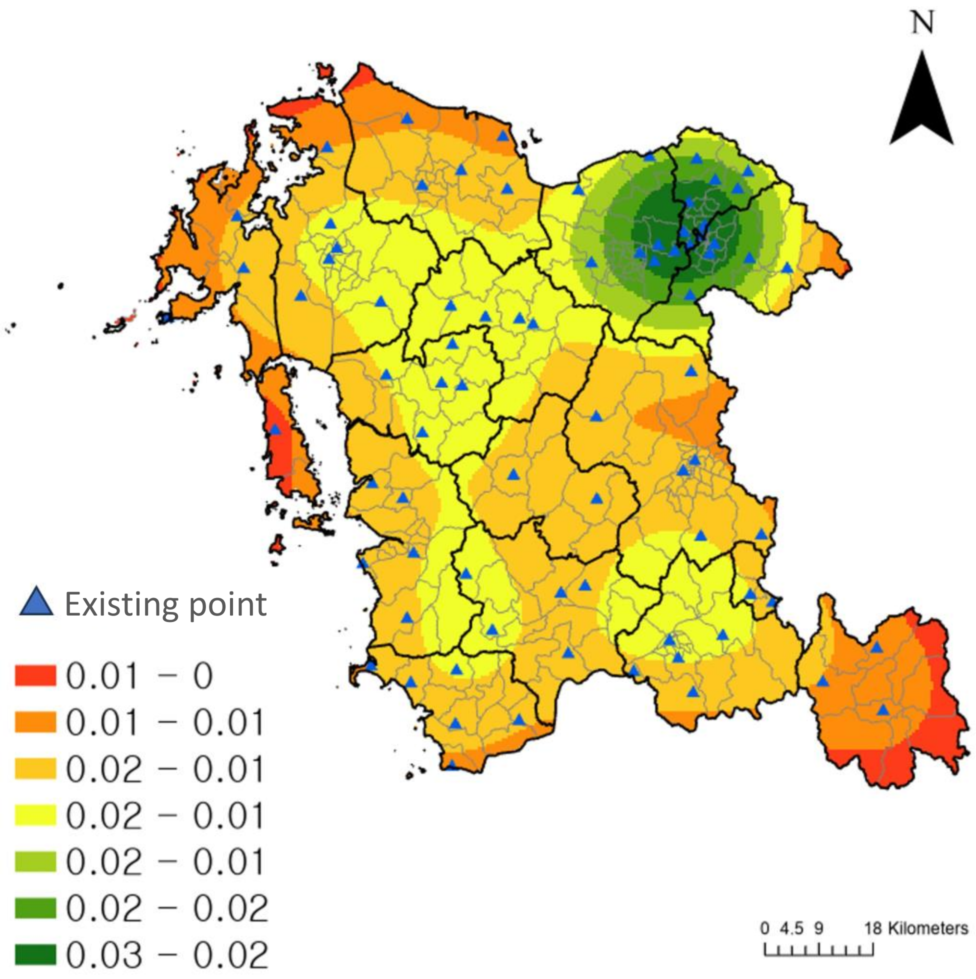
Increase or decrease the optimal number by region



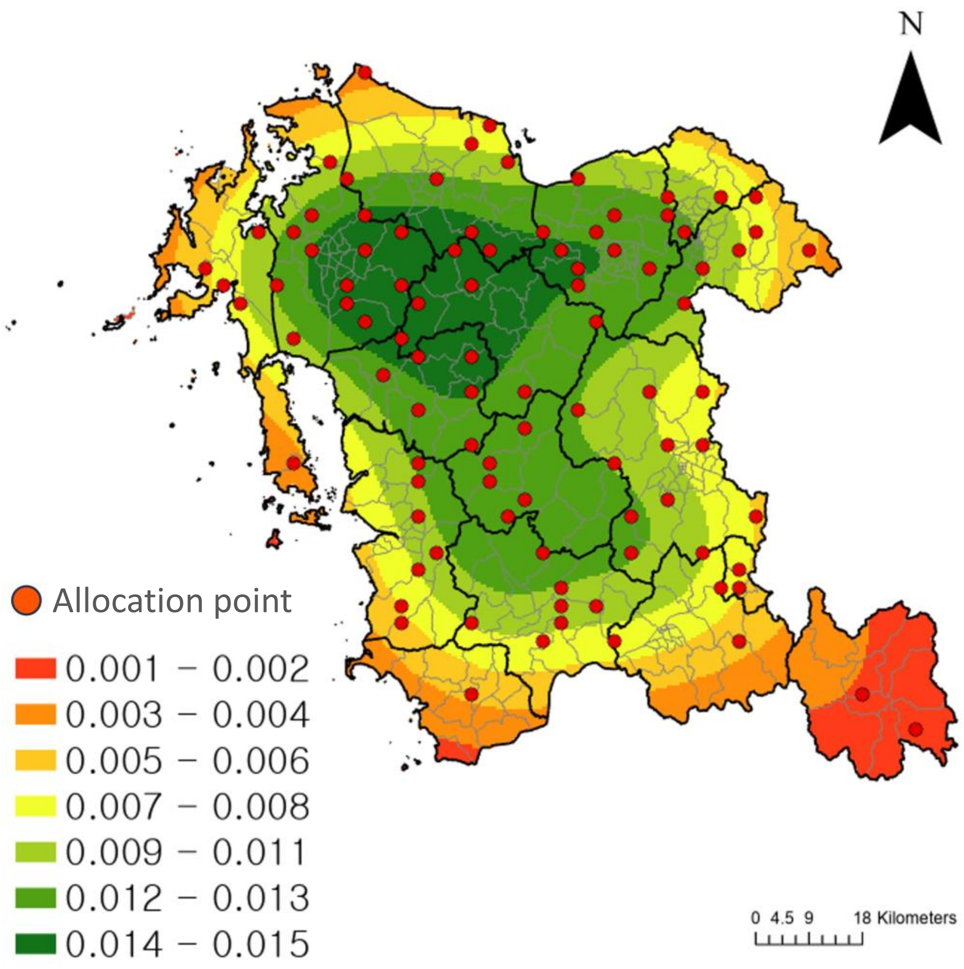
Maximum Coverage Location Problem

Optimization Results

Supply density of existing centers



Supply density of optimization center



Discussion & Conclusion

Spatial-Temporal GCN

- ***ST-GCN predicts response times*** based on administrative divisions, seasons, time slots, accident types, and locations, ***offering regional insights to enhance emergency services***.
  - Results predict that certain regions may have higher predicted response times. This indicates potential challenges in accessibility and suggests the need for policy interventions.
  - Fire incidents exhibit the highest predicted response times, underlining the need for enhanced fire prevention and response measures, particularly in vulnerable areas.

Discussion & Conclusion

Maximum Coverage Location Problem

- ***MCLP focuses on efficiently distributing resources*** to areas most needed, ensuring maximum coverage while considering the importance of demand points.
  - Variances are notable across regions, particularly in Seobuk-gu and Seocheon-gun, where unnecessary fire stations are optimized, enhancing resource efficiency and indicating previous station overplacement in these areas.
  - Comparing the placement of existing and optimal fire stations illuminates supply density disparities, particularly in rural areas, underscoring the need to enhance emergency service availability beyond urban centers.

Discussion & Conclusion

Implications

- ***Data-driven policy making***
  - Data-driven analysis can identify regional emergency service gaps and improve the quality of emergency medical services.
- ***Establishment of regional emergency medical service focus policies***
  - Focused policies are needed that consider each region's vulnerable characteristics and changes in emergency service response times.
- ***Finding ways to deploy emergency medical service resources optimally***
  - Future research could develop a model that considers the number of ambulances at each center to reflect precise supply and demand.

Discussion & Conclusion

Limitations & Future Study

Limitations on demand forecasting points

- Since the emergency medical service demand points used in the analysis are merged at the 'Eup/Myeon/Dong' (township levels), accurately predicting demand points is limited.
- Improving the precision of prediction points by utilizing point data for more accurate demand point prediction is necessary to overcome this.

Limitations on Optimization Model

- MCLP results do not consider the number of ambulances operating at the 119 centers and the size of the population.
- We plan to develop the MCLP model that considers capacity in future research.

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