Research Square

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# Development and validation of methods to predict ground- and helicopter-based emergency medical service travel times

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**Research Article**

**Keywords:**

**Posted Date:** June 13th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-9854465/v1

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**Additional Declarations:** No competing interests reported.

# Abstract

### Background

Helicopter-based Emergency Medical Services (EMS) are expensive and should only be deployed when they provide substantial benefits to patients. One such benefit is a more rapid response to incidents and transport to hospital compared to Ground-based EMS. This study evaluates methods for estimating response times for the purpose of optimizing the selection of helicopter vs. ground EMS.

### Methods

Ground EMS travel times were estimated using an open-source routing tool, the estimates of which were adjusted using linear regression and gradient boosting models based on historical travel times. Helicopter travel times were similarly estimated based on great circle distances adjusted by historical data. Models were evaluated using several measures of predictive accuracy to enable comparison with other studies.

### Results

In validation data collected after finalization of the methods, prediction models for Ground EMS travel times explained a substantial portion of variation in drive times to location and to hospital ($R^2$ 0.75 and 0.68 respectively), and somewhat less for helicopter response times ($R^2$ 0.51 and 0.32 respectively). Mean average percentage error was ca. 20% for all investigated estimation techniques and times.

### Conclusion

Integrating tools based the open-source code provided with this study has the potential to improve the ability of dispatchers to estimate relative travel times and direct the most appropriate resources to a given patient.


# Background

Helicopter Emergency Medical Services (HEMS) are a costly and finite resource that should be deployed when they offer a clear advantage over ground EMS (GEMS). One such advantage is shorter response times, which have been associated with improved patient outcomes across multiple acute conditions (1–8). However, determining when HEMS is faster than GEMS for a given incident is not straightforward, as response times depend on multiple factors including distance, road quality, weather, traffic, ambulance availability, and station placement (5, 9).

Several studies have compared GEMS and HEMS response times, generally showing that HEMS are faster over longer distances, and in many cases provide shorter total transport times to definitive care (4, 10–12). Some studies have attempted to define geographical cutoffs for when HEMS should be

dispatched over GEMS (11, 13), but these cutoffs tend to be context-specific and difficult to generalize to other EMS systems (14).

Current HEMS dispatch criteria are based primarily on estimated clinical need (15–17), and physician-staffed HEMS has demonstrated a severity-adjusted mortality benefit compared to GEMS (18–20). However, even in the absence of a need for more advanced prehospital interventions, dispatching HEMS to shorten time to scene or time to hospital may benefit *patients in the highest-priority dispatch category.* Some systems already incorporate transport time predictions into dispatch decision-making (21).

Prediction models for EMS planning have been explored previously (22, 23). One study using a machine learning algorithm to predict GEMS response times in Stockholm found low overall correlation with actual times, though correlation was better among high priority dispatches (9). A generalizable, easily implementable method for estimating and comparing GEMS and HEMS response times remains lacking.

We hypothesized that it would be possible to develop a method for accurately estimating GEMS and HEMS response times, and that such a method could identify a geographical threshold at which HEMS outperforms GEMS. We further aimed to provide open-source code that could be readily implemented in other prehospital systems to support dispatch optimization.

Aim

To develop and validate methods for estimating ground and helicopter-based EMS travel times, with the goal of identifying potential time savings enabled by dispatching a helicopter.

# Methods

Study design

A single-center model development study with validation in a dataset collected subsequent to the finalization of the models.

Study setting

This study was conducted in Uppsala, Sweden, a mixed urban-rural region spanning 12 173 km and containing 410 572 residents in 2025. The region is serviced by a single regional, hospital-based EMS agency fielding 13 daytime ambulances across 4 ambulance stations and an additional 4 consistently manned stand-by posts. HEMS responses are provided by a single hospital-based intensive care HEMS service based near the main hospital to which the majority of critical patients are transported. HEMS is typically dispatched based on indication by the nurse staffed Emergency Medical Dispatch center responsible for prehospital care in the region. Ground EMS are staffed by at least one nurse and either a second nurse or an emergency medical technician, while HEMS units are staffed clinically by a medical doctor and a nurse. The analyses performed in this study generally assume simultaneous dispatch of HEMS and GEMS resources.

Data collection

Data for model development was collected from the dispatching system in Region Uppsala for the years of 2022 to 2024, supplemented by data collected from HEMS flight logs. Ground ambulance missions were filtered to include only missions with a priority 1 (lights and sirens) response. In analyzing transport times to the hospital, only those relating to priority 1 patient transports were included. GEMS missions missing a documented ambulance starting point were excluded, as well as missions with an at-scene time of less than 1 minute or more than 3 hours, as these were generally the result of documentation errors by ambulance crews. Hourly data on temperature, wind, precipitation, snow depth, and sight distance was downloaded from The Swedish Meteorological and Hydrological Institute (24). Subsequent to finalization of the travel time prediction models, similar data was collected for 2025 to serve as a validation dataset. Data collection for this study was approved by the Swedish Ethics Review Authority (dnr 2024-08307-01).

Travel time prediction

Baseline travel time and distance estimates for ground ambulance missions were generated using the Open Service Routing Machine (OSRM) (25). Using this tool, the distance and estimated drive time from the starting point to the incident location, as well as from the incident to the receiving hospital was estimated. Baseline travel distances for HEMS missions were estimated based on Great Circle distances between the starting location and incident, and between the incident and hospital using the *sf* R package (26).

These baseline times and distances were then used as predictors in four linear regression models estimating travel time as a function of the baseline distance and time (including an interaction effect to capture potential differences in estimated and actual driving speed across road types), mission priority (higher acuity 1A or lower acuity 1B), time of day (using a sin and cosine transformation to capture variation across the day and including an interaction with the distance and time terms), the starting location of the call, the type of call (Medical, Trauma, or traffic accident), and the distance of the incident to the nearest road included in the OSRM road network data. Weather variables were similarly included as linear predictors in the HEMS models, and interactions with drive time estimates were included in the GEMS models. In addition to the linear regression models, estimates based on non-parametric gradient boosting were generated using the XGBoost package, with all interactions and non-linear effects handled natively by the machine learning algorithm.

# Statistical analysis

Predicted travel times estimated as described above in data from 2022–2024 were compared with actual travel times in the 2025 validation dataset to evaluate model accuracy. To enable comparison with other research, model performance was evaluated in terms of multiple performance metrics including absolute deviation, Mean Average Percentage Error (MAPE), $R^2$ value (i.e. proportion of variation in travel times explained by the predictions), and Root Mean Square Error (RMSE). Scatterplots were used to

visualize predicted vs true travel times to evaluate calibration. Travel times were visualized geographically by plotting travel times on a map using thin plate spline regression to interpolate response times between observed values using the *fields* R package (27). Descriptive statistics were generated using appropriate measures of central tendency and 1000 bootstrap replicates were used to generate 95% confidence intervals. All analysis was performed using R v 4.4.2 (28) and all code and models used to perform this analysis is included as Supplementary material 1, and is available in the online repository associated with this study (29).

# Results

A total of 24 756 incidents were identified meeting the study inclusion criteria, of which 527 were responded to by HEMS. The characteristics of these incidents are provided in Table 1 below. It may be seen that HEMS missions tend to be higher priority, more often related to trauma and traffic accidents, and are further away from both the nearest ambulance station and from the main receiving hospital.

Table 1
Descriptive statistics

| | **Ground EMS** | | **Helicopter EMS** | |
|---|---|---|---|---|
| | **Training set** | **Validation set** | **Training set** | **Validation set** |
| Number of included incidents | 17604 | 6546 | 323 | 204 |
| Percent priority 1A | 7.6 (7.2–7.9) | 7.6 (7-8.3) | 41.8 (36.5–47.7) | 37.7 (31.4–44.1) |
| Percent Medical incidents | 86.3 (85.7–86.8) | 86.3 (85.5–87.1) | 58.5 (53.3–64.1) | 64.2 (57.8–70.6) |
| Percent Trauma incidents | 11 (10.5–11.4) | 11.2 (10.4–12) | 23.2 (18.6–28.2) | 24 (18.1–30.4) |
| Percent Traffic Accident incidents | 2.8 (2.5-3) | 2.5 (2.1–2.9) | 18.3 (14.2–22.6) | 11.8 (7.8–16.7) |
| Mean driving distance to incident (km) | 10 (9.9–10.2) | 10 (9.7–10.2) | 19.8 (18.6–20.9) | 21.2 (19.7–22.8) |
| Mean driving distance to hospital (km) | 27.7 (27.3–28.1) | 26.5 (25.9–27.1) | 55.2 (52.8–57.6) | 50.8 (47.7–54.2) |
| Mean time to location (minutes) | 10.8 (10.7–10.9) | 10.7 (10.5–10.8) | 23.5 (22.7–24.4) | 22 (21-23.1) |
| Mean time to hospital (minutes) | 53.2 (52.6–53.8) | 52.8 (51.8–53.9) | 64 (62.1–66) | 62.7 (59.7–65.5) |

Mean / Percentage values are presented with bootstrapped 95% Confidence Intervals

Prediction models

Gradient Boosting (GB) and Linear regression Models (LM) were fit to estimate travel times to the incident and the total time to hospital for GEMS and HEMS respectively. The characteristics of each of these models are presented in Table 2 below, and the full model specification for each may be found in supplementary materials 1. The GEMS models had a generally high degree of explained variance, while there was more unexplained variability in the HEMS models. The models were able to predict travel times to the incident with an average absolute error of ca. 1.7 minutes for GEMS and 4.6–4.8 minutes for HEMS, with greater errors estimating total time to hospital. As a percentage of the total time however, all models performed similarly, with mean average percentage errors of around 20%. In terms of $R^2$, the models tended to capture more of the variation in the data regarding GEMS (69%-76%), than for HEMS missions (25%-39%).

Table 2
Model performance characteristics

| type | destination | method | Mean true time | absolute deviation | Mean average percentage error | $r^2$ | rmse |
|---|---|---|---|---|---|---|---|
| GEMS | To hospital | GB | 52.8 | 8.54 | 17.8 | 0.704 | 12.16 |
| | To hospital | LM | 52.8 | 8.76 | 18.8 | 0.703 | 12.18 |
| | To location | GB | 10.7 | 1.57 | 17.2 | 0.793 | 2.82 |
| | To location | LM | 10.7 | 1.68 | 19.2 | 0.774 | 2.95 |
| HEMS | To hospital | GB | 62.7 | 11.36 | 18.9 | 0.245 | 15.11 |
| | To hospital | LM | 62.7 | 11.04 | 19.1 | 0.287 | 14.19 |
| | To location | GB | 22 | 4.63 | 22.6 | 0.387 | 6.58 |
| | To location | LM | 22 | 4.86 | 24.5 | 0.386 | 6.68 |

GEMS: Ground Emergency Medical Services, HEMS: Helicopter Emergency Medical Services

For each of these models, plots of predicted vs. true historical response times were plotted to reveal patterns in model predictions as shown in Fig. 1. As may be seen in the figure, the predictions generally fit true values well, though some extreme low and high travel time values exist which are not well characterized by the models, though these may also be due to mis-documented times.

*Each dot represents a travel time prediction and true value, with the red diagonal line representing the line of perfect fit. Lines of best fit are drawn for each model to illustrate calibration. GB: Gradient Boosting, LM: Linear Model*

Figure 2 illustrates the relationship between the road distance to the incident/total distance travelled to the hospital. While there is substantial variability stemming from other variables accounted for in the models, it may be seen that benefits in terms of time reductions become apparent around 50 km. Note

also the non-linear behavior of the GB models at short to-hospital distances, stemming partly from the lack of observations for HEMS responses at these short distances.

The model predictions may finally be used to compare the difference in travel times geographically, estimating travel times using the models for each ground and helicopter mission. The resulting travel time differences based on the prediction models may be compared to differences between travel times directly interpolated from historical data, as shown in Fig. 3:

*Travel time estimates interpolated using thin plate splines, with black dots representing the location of ambulance stations and the blue dot representing the location of the helicopter base. The main receiving hospital is co-located at the black dot near the helicopter base. Predictions of the Gradient Boosting (GB) and Linear Regression model (LM) are shown separately.*

It may be seen that while the empirically generated and predicted travel time difference estimates generally coincide well, there are some discrepancies, e.g. in the far east and north of the region. Overall, there are few parts of the region where a HEMS response generally reduces response times to incidents, although substantial areas in the northwest and northeast where HEMS has the potential to substantially reduce transport times to the hospital.

## Discussion

The prediction models we present provide a highly predictive method for estimating EMS arrival times. The models generally explained more of the variability in GEMS times than HEMS times, and in prospective application, both regression and gradient boosting-based approaches had similar levels of accuracy. As applied to the studied region, there were few geographic areas where HEMS has an overall potential to reduce incident response times, but in many outlying areas, reductions in total prehospital times of over 10 minutes could be expected, with substantial expected benefits in terms of time savings beginning at road travel distances of around 40 km to incidents, and at 50 to 60 km of total road travel distances to hospital. Per most evaluation metrics, the models had a greater ability to predict GEMS times than HEMS times, which may be due to the more detailed routing data available in estimating GEMS times, and to more substantial variability in both HEMS preparation time and on-scene time stemming from e.g. the number and intensity of interventions performed by HEMS crews (30).

We compared two approaches to estimating prehospital times, using a traditional linear regression approach and a non-parametric machine learning algorithm. Both approaches had similar predictive accuracy, with a slight edge for the non-parametric GB approach per most metrics. While regression modelling requires some thoughtfulness in considering which interaction and non-linear effects to include (which is not necessary using the machine learning approach), it is also more consistent in training and validation data, and may extrapolate better to new situations (e.g. missions with very short transport distances as suggested by the clustering seen in Fig. 2). While the weather-related parameters added a small amount of predictive value (constituting a larger proportion of the models total explanatory power for HEMS times), model performance is primarily based on geographical and

temporal data, and these auxiliary predictors may not be worth the additional complexity necessary to incorporate them in a real-time predictive tool. A full accounting of the importance of each included variable may be found in Supplementary materials 1.

The performance of the models reported here can be difficult to compare with other approaches, given the strong influence of the study setting on model performance. The $R^2$ of 0.77 for the GEMS incident response time model compares favorably with that developed by Hill et al. which achieved an $R^2$ of 0.37, although those results also included lower-priority calls (9). The MAPE of 17.8/18.8% (for GB and LM models respectively) for patient to-hospital times found here similarly outperformed the 45% MAPE reported by Abid et al. (31). Similarly, the MAPE for to-incident times of 17.2/19.2% identified here compares favorably to the 25% identified by Fleschman et al. (32). Meanwhile, the model proposed by Westgate et. al. achieved a substantially lower RMSE (72 seconds vs. 198 as found here), though these results were identified in the highly restrictive context of urban Toronto with response distances of < 5 km (22). We identified no previous literature attempting to predict HEMS prehospital times, and thus lack benchmarks regarding the performance of our approach. Stassen et al. however investigated the distance at which a HEMS response is warranted in the context of HEMS requested by on-scene GEMS, which contrasts with the setting of this study in which GEMS and HEMS are typically dispatched simultaneously. Stassen et al. identified a driving distance of 119 km at which HEMS results in reduced incident to hospital times, which corresponds roughly to our findings of a cutoff of 50 km given that our results include GEMS drive times both to and from the incident (33).

We encourage researchers to make use of the source code provided with this study and further develop the methods we report. Further efforts may for instance include the use of real-time traffic data which would could improve in the GEMS model fit.

Limitations

The use of HEMS in primary incident response is motivated not only by shortened prehospital times, but also by the enhanced competencies provided by on-scene medical doctors typically found on HEMS units. As such, findings relating to low potential for time savings in incident responses should not be construed as an argument against the impact of on-scene HEMS care overall.

It should also be noted that there may be differences in the duration of the interval from the documented time of arrival to the hospital until the patient arrives to definitive care. In our setting, GEMS units deliver the patient directly to the Emergency Department, while HEMS units must transport the patient from the helicopter landing pad, which can add up to 10 minutes to the total time it takes for a patient to be handed over to definitive care. While we lack data to model these intervals, in a practical application they could be represented by adding a flat time penalty to the estimated helicopter transport time.

Several methodological limitations should be noted. Data were restricted to high priority missions transported to the primary regional hospital, limiting generalizability to other transport modes and destinations. It may also be noted that especially at the extreme high end of travel times, travel times

tended to be under-estimated, although the possibility of these extreme values being due to documentation errors cannot be excluded. It was noted that the volume of HEMS responses was substantially higher in the validation dataset, though this was verified as reflecting a true increase in the number of primary HEMS responses. While we provide the models reported here for demonstration purposes, any real implementation of our methods should be done after re-training the models based on data collected in the local context.

# Conclusion

The open-source methods presented here provide estimates of GEMS and HEMS pre-hospital times competitive with state of the art methods. If implemented in clinical practice, these estimation techniques could serve as an effective decision support tool for dispatchers to aid in determining the potential clinical benefit in terms of reduced transport times of directing HEMS resources to a given patient.

# Abbreviations

EMS
Emergency Medical Services
HEMS
Helicopter Emergency Medical Services
GEMS
Ground Emergency Medical Services
OSRM
Open Service Routing Machine
MAPE
Mean Average Percentage Error
RMSE
Root Mean Square Error
GB
Gradient Boosting
LM
Linear regression Model

# Declarations

### Ethics approval and consent to participate

Study was approved by the Swedish Ethics Review Authority (dnr 2024-08307-01), which waived the need to obtain informed consent for participation in the study.

### Consent for publication

Not applicable

## Competing interests

The authors declare that they have no competing interests.

## Funding

No specific funding was provided for this study.

## Author Contribution

DSp and AB conceived of and designed the study. JS, JA and DS performed data collection. DSp performed the analysis, generated figures and tables, and drafted the manuscript. DSm and JT provided clinical and operational context for model functionality. All authors reviewed and provided meaningful input to the manuscript, and approved it's final form.

## Acknowledgement

The thank the clinical staff at the ambulance service, HEMS, and emergency dispatch center for their tireless work in providing high quality medical care, and generating the underlying data for this study.

## Data Availability

Access to individual level data is available to researchers with appropriate Swedish ethics approval upon contact with ambulanssjukvard@akademiska.se. All code necessary to replicate the results is available in an online repository at https://doi.org/10.17605/OSF.IO/NUGV4

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# Figures

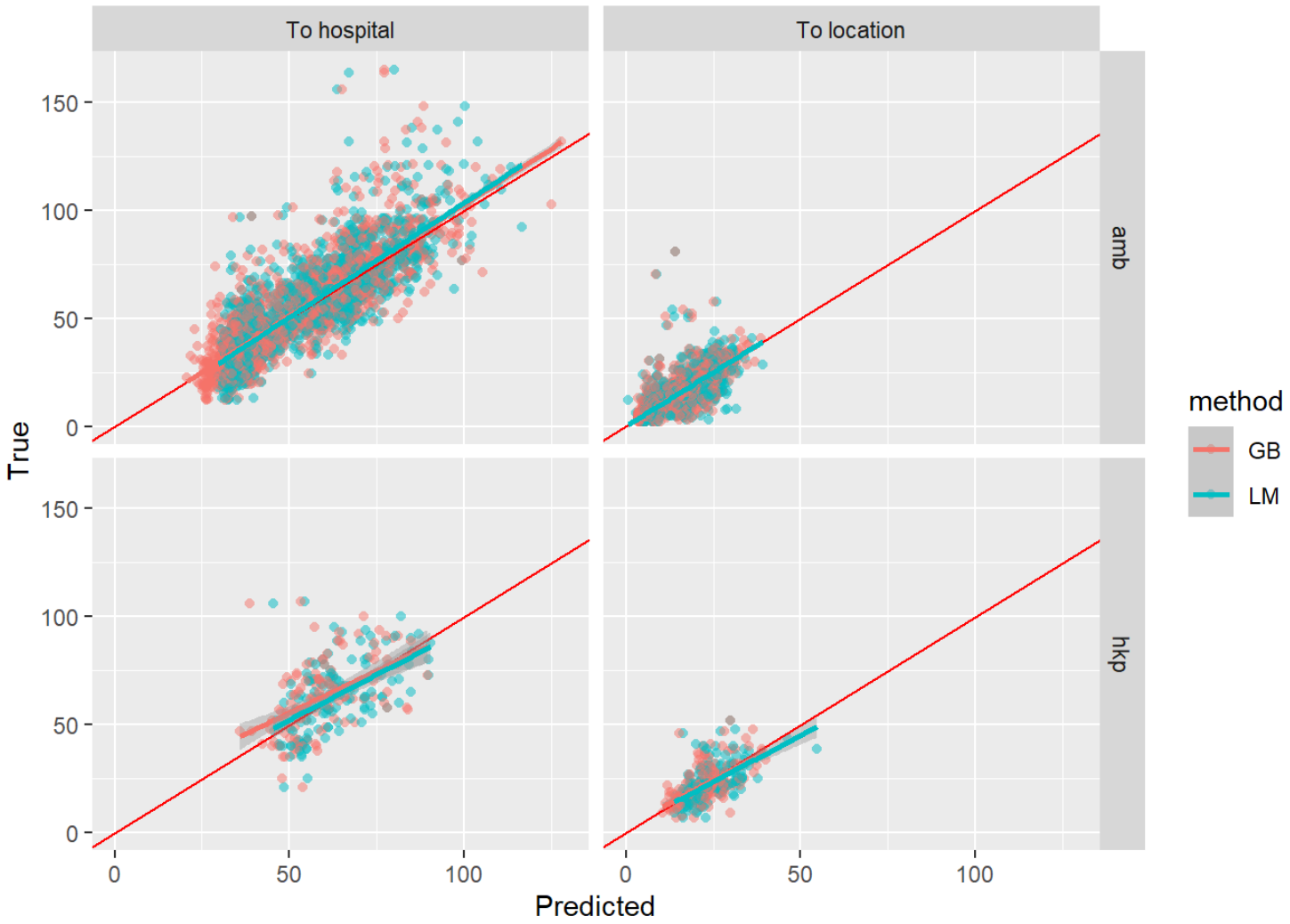



**Figure 1**

Predicted vs true travel times
Each dot represents a travel time prediction and true value, with the red diagonal line representing the line of perfect fit. Lines of best fit are drawn for each model to illustrate calibration. GB: Gradient Boosting, LM: Linear Model

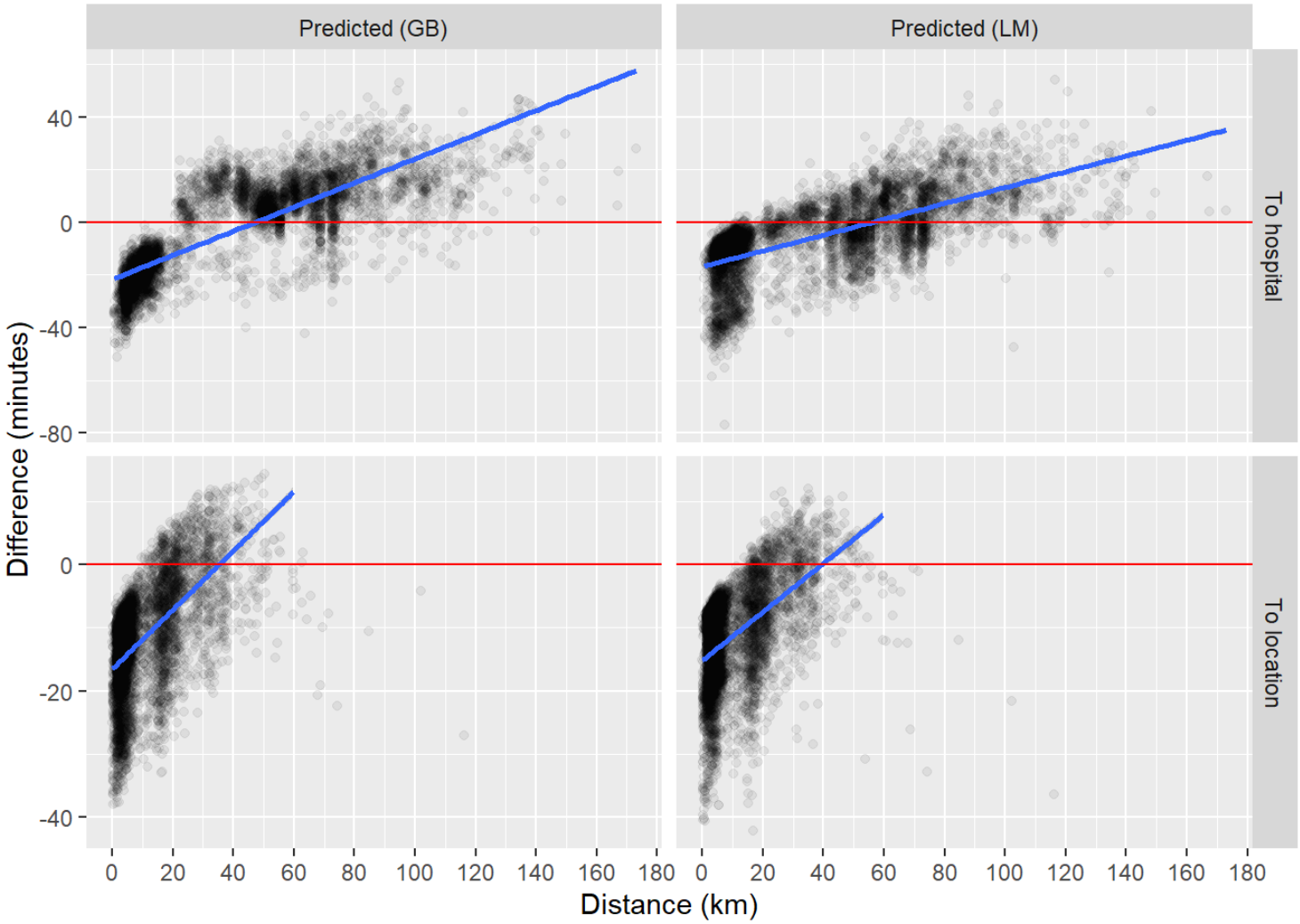



**Figure 2**

HEMS vs GEMS time gain vs road distance travelled GB: Gradient Boosting, LM: Linear Model

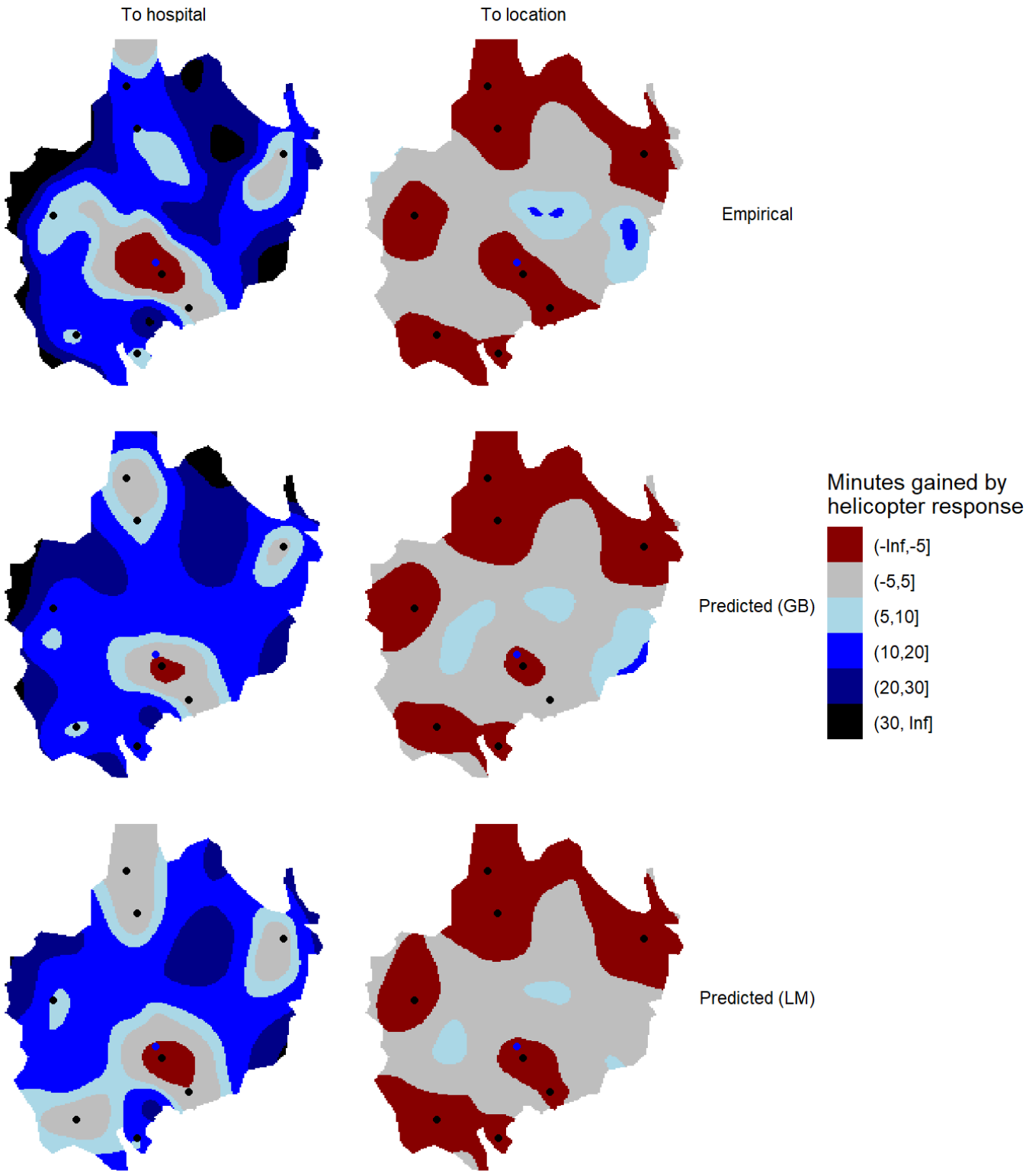



**Figure 3**

Predicted and empirical travel time differences between ground and helicopter EMS
Travel time estimates interpolated using thin plate splines, with black dots representing the location of ambulance stations and the blue dot representing the location of the helicopter base. The main receiving hospital is co-located at the black dot near the helicopter base. Predictions of the Gradient Boosting (GB) and Linear Regression model (LM) are shown separately.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- supplement1analysisnotebook.html