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6G Visible Providing Advanced Weather Services for Autonomous Driving

Timo Sukuvaara [1,*], Kari Mäenpää [1], Hannu Honkanen [1], Ari Pikkarainen [1], Heikki Myllykoski [1], Virve Karsisto [2] and Etienne Sebag [3]

[1] Arctic Space Centre, Finnish Meteorological Institute, 99600 Sodankylä, Finland; kari.maenpaa@fmi.fi (K.M.); hannu.honkanen@fmi.fi (H.H.); ari.pikkarainen@fmi.fi (A.P.); heikki.myllykoski@fmi.fi (H.M.)
[2] Meteorological Research, Finnish Meteorological Institute, 00101 Helsinki, Finland; virve.karsisto@fmi.fi
[3] Department of Mathematics and Statistics, University of Helsinki, 00101 Helsinki, Finland; etienne.sebag@helsinki.fi
* Correspondence: timo.sukuvaara@fmi.fi

Abstract: Business Finland 6G Visible project's objective is the development of 6G-era service and architecture solutions utilizing autonomous and semi-autonomous driving, with both physical and logical computational elements and with use cases for real-life verification and validation. Finnish Meteorological Institute is focusing especially on weather- and safety-related services for autonomous vehicles. We are tailoring our road weather services for the special needs of autonomous driving, keeping in mind that autonomous vehicles are more sensitive to the harsh winter weather conditions and benefit from more accurate weather information considering the sensor systems of each vehicle. Employing weather radar-based nowcasting of more accurate short-term precipitation forecasting benefits autonomous traffic, especially in cases of heavy local precipitation by re-routing/route planning and avoiding heaviest precipitation. Evaluation of autonomous vehicles' sensor systems' sensitivity to harsh weather conditions allows for weather forecasting based on the real vulnerability of each vehicle.

Keywords: 6G; 5G; V2X; autonomous driving; road weather; nowcasting; LiDAR

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1. Introduction

Self-driving and autonomous vehicles have been a focal point of development for some time. Waymo, the company spun out of Google's self-driving car research, launched a commercial autonomous level 4 taxi service by late 2018, along with parallel competitive solutions [1]. Autonomous level 4 means otherwise fully autonomous operations, but the driver should always be able to take over the driving. Even today, no fully autonomous level 5 system is in operative use, but various deployments of autonomous operative vehicle with monitoring personnel onboard exists. Autonomous driving in motorways is widely studied and tested as well, and the special demands regarding the road infrastructure have been evaluated in [2].

As there are multiple solutions for autonomous driving, there are also many solutions for sensor systems in autonomous traffic. Positioning systems, along with vehicle radars, LiDARs, sonar systems and traditional video cameras, are the most common approaches for sensors, along with combined solutions [3,4]. The operation of radar and LiDAR sensors in different weather conditions has been estimated in [5]. Autonomous driving operations in winter conditions, when road surface markings, etc., are not visible, have also been studied and evaluated [6].

Current technical solutions for autonomous vehicles already provide precision and reliability sufficient for many applications. However, there are still many limitations considering the detection of varying weather conditions and the use of real-time observations of the environment. Autonomous vehicles are sensing the environment in an entirely different way than a human driver and are critically more sensitive in some special weather conditions. Thus, autonomous vehicles require specially tailored road weather forecasts for situations where the sensors are not expected to work properly. There is a need for a real-time dynamic information environment that includes adaptation to weather conditions. Moreover, incorporating knowledge about road traffic accidents is pertinent because vehicular crashes pose a fundamental safety risk, especially during the winter months when roads tend to accumulate snow and ice. Having a deeper understanding of how the probability of a road incident varies with certain meteorological and spatiotemporal factors is useful to increase awareness of weather-related road safety.

In the 6G Visible (Seeing Invisible as a 6G infrastructure Service for Autonomous Vehicles) project [7], Finnish Meteorological Institute (FMI) and the University of Oulu are joining forces to improve intelligent traffic road weather services for autonomous driving. The key objectives of the project are the development of 6G-era service and architecture solutions utilizing autonomous and semi-autonomous driving as the case service, and with real-time-intensive and safety-critical services, it validates a 6G network technologies' support for largely distributed, real-time-intensive and safety-critical services. Today, the software development of distributed systems is dominated by the cloud paradigm, in connection to edge-based and local computing entities (an optional addition to IoT devices). The 6G technology will offer an improved means for application development, integrating the development of heterogeneous systems that include software platforms, cloud, big data, AI, edge, IoT, and quantum computing. The strategic research and innovation agenda in Finland for beyond 5G and 6G describes a national development roadmap for advancing Finnish 6G competencies [8]. This project contributes to the strategic research's overall goals of performance/performance demands and sustainability of 5G-A(5G-Advanced) and 6G networking.

The main target of the project is dynamic real-time modeling of the environment and obstacle detection for autonomous or semi-autonomous vehicles, but FMI will focus especially on road weather-related goals in this context. How could we enrich the road weather services to better aid autonomous driving? Could we consider the different sensors' vulnerability to certain weather conditions and provide more accurate warnings? And could we use autonomous vehicles' sensors as a source of road weather information?

To answer these research questions, we are focusing in this paper on the following issues: (1) evaluation of LiDAR and camera sensors used in autonomous vehicles to estimate their sensitivity to different weather conditions and especially seeking vulnerabilities; (2) evaluation of V2X communication systems used in Intelligent traffic to find the best ways to provide autonomous vehicles with up-to-date weather warnings and collect data on road conditions; (3) road weather forecasts adjusted for autonomous vehicles and enriched with short-term nowcasting forecasts to offer enhanced safety; (4) route planning with knowledge modeling based on weather and other parameters; and, finally, (5) predictive modeling of weather-related crashes for building a statistical background for the services. These issues are considered in the following chapters of this paper, supplemented with an evaluation of the methods and concluding remarks.

2. Evaluation of Autonomous Vehicle LiDAR and Camera Sensor Sensitivity to Harsh Weather

To estimate the autonomous vehicle sensors' sensitivity to harsh weather, we composed a fixed measurement system for our winter testing track. The Sod5G test track is in Sodankylä, Northern Finland, and is used as a testing and development environment for intelligent traffic, autonomous vehicles, and road weather services [9]. The test track is supplemented with a multitude of communication systems, e.g., vehicle-to-vehicle (V2V) radios for ITS-G5 and C-V2X, a WiFi6 hotspot, and 5G test networks. All of FMI's special instrumentation and knowledge related to intelligent traffic road weather services are employed as part of the 6G Visible development architecture.

In this work, autonomous vehicles' sensor systems are being evaluated for their sensitivity to harsh weather conditions. For this purpose, FMI employs a self-built, small, autonomous robotic platform to study the instrumentation used for autonomous vehicles. However, to evaluate the weather dependency, we are interested in having measurements in a fixed environment, with all environmental parameters known. Special focus will be placed on LiDAR and camera sensor instruments, and vehicular radar systems are part of the future work. We are studying LiDAR's vulnerability to weather in the tasks of (1) road sign recognition, (2) identifying snow cover, and (3) snowbank height monitoring. LiDAR and a camera are installed into the wall of the hub (Figure 1) and monitor the same location on the track, where two traffic signs, the snow cover, and the snowbank height are all visible. Parallel images from LiDAR and the camera are shown in Figure 2 in their test locations. The LiDAR instrument used is the mid-range Ouster OS1 lidar sensor features a 90 m range on a dark 10% target, a 42.4° vertical field of view, and high reliability for the most rugged conditions. It is designed for all-weather environments and use in industrial automation, autonomous vehicles, mapping, smart infrastructure, and robotics [10]. The camera instrument used is a standard security monitoring camera device. The LiDAR is also used in our miniature autonomous vehicle platform to perform on-board measurements and 3D mapping of the test track, but the weather vulnerability evaluation is based on fixed installation only.

Figure 1. Vehicle LiDAR and camera in parallel installation.

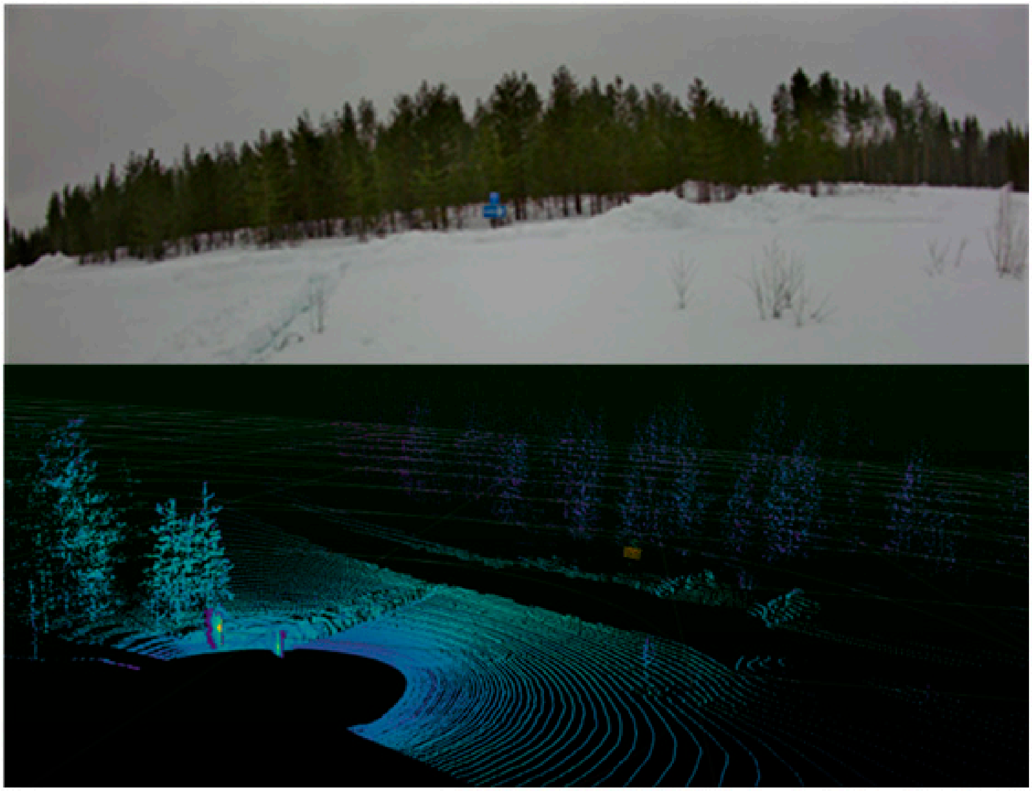

Figure 2. Example of parallel camera (above) and LiDAR measurement. There are two traffic signs in the middle with infrared coatings, visible as yellow in the LiDAR figure.

The measurement system collects parallel measurements from LiDAR and the camera in a one minute-interval, which then go into temporary storage. Whenever the weather conditions become challenging for some imaging system, the images of that case will be saved for permanent storage. In addition, the road weather information collected from test track road weather stations and local road weather forecast information is stored as well [9]. As soon as we have comprehensive material from different harsh conditions, we can conduct an estimation of the vulnerability of our sensors.

3. Communication with Autonomous Traffic

To export sensor data from autonomous traffic (as well as any other vehicles) and import real-time weather- and safety-related warnings (presented later in this paper), a proper communication system available within the whole traffic entity is required. Cellular communication with 5G is currently commonly available in Finland and, therefore, is considered as the primary approach. However, there are also methodologies especially designed for short-range traffic entity communication, called V2X (Vehicle-to-Everything) communication, based on European ITS-G5, inherited from IEEE 802.11p standard and C-V2X [11]. These approaches can also be used in parallel as a hybrid communication system. Such approaches within the realm of road weather and safety services have been studied in [12].

Naturally, general Wi-Fi communication can be employed, as well as satellite communication, at least as a complementary communication system for 5G cellular networking. All of these communication systems are available at the Sod5G test track and were evaluated as candidate communication entities for the 6G Visible operational entity. The primary approach is to rely on commercially available communication system with adequate coverage within the public road network, which is, in our case, 5G cellular networking, with supplemental 4G cellular networking in some (rural) areas where 5G is not available. However, alternate solutions with ITS-G5 and C-V2X are studied in the test network area, as they present alternative approaches if the required service availability can be achieved through specified user density in public traffic.

4. Road Weather Forecasts and Precipitation Nowcasting

FMI produces road weather forecasts during the project for the Oulu pilot area (Figure 3). The forecasts are generated with the FMI road weather model RoadSurf [13]. This is one-dimensional heat balance model that forecasts road surface temperature, friction, and road condition (wet, icy, snowy. . .). As input, the road weather model requires atmospheric forecast data from a numerical weather prediction model. Data from an MEPS (MetCoOp Ensemble Prediction System) [14] control member are used as the input to the model in this project. The road weather forecast points are in 50 m intervals along the major roads. The forecasts are updated every hour.

Figure 3. Piloting area for road weather forecasts (red routes in the map). Made with Natural Earth (https://www.naturalearthdata.com/).

Laser scanning data produced by national land survey of Finland were used to determine the sky view factors to each forecast point. The sky view factor means the area of the sky that is visible from the road point. Road points on open fields have larger sky view factors than road points surrounded by forests. RoadSurf uses sky view factors to adjust the incoming and outgoing radiation [15]. In addition, laser scanning data were used to determine local horizon angles to each direction in the forecast points. These were used by the shadowing algorithm in the road weather model. If the local horizon angle was larger than the sun elevation angle at the direction of the sun, then the road point was in shadow, and the direct solar radiation was set to zero in the model. Figure 4 shows an example of friction forecast to the pilot area on 29 March 2024. Snow on the road causes low friction values, except in the southern part of the area.

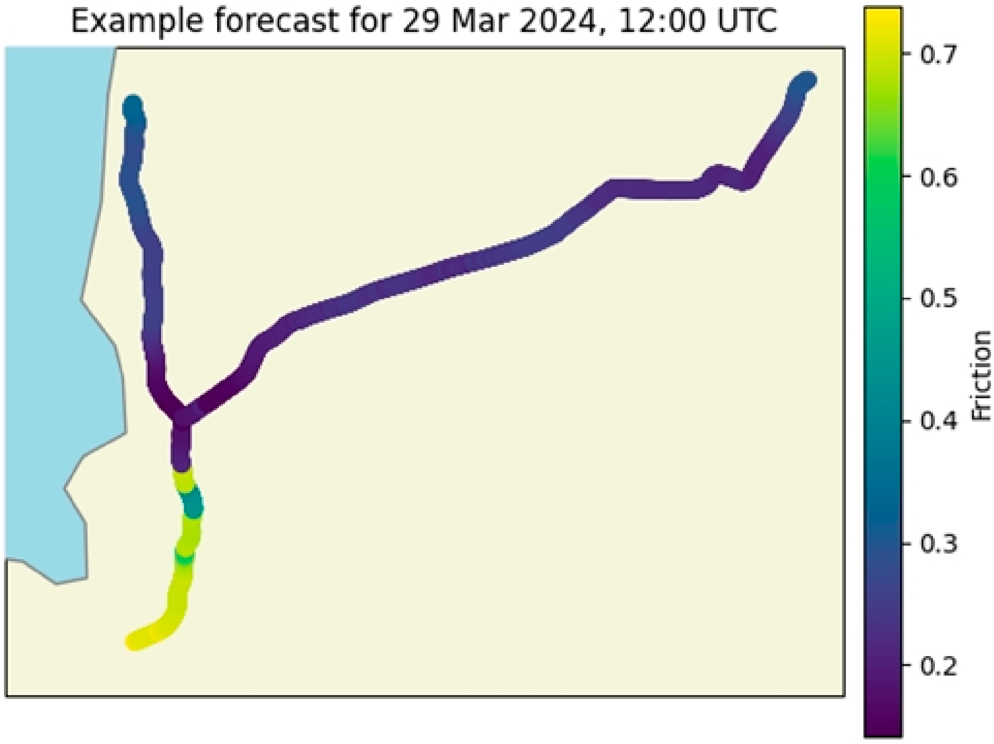

Figure 4. Example friction forecasts for pilot routes for 29 March 2024 12 UTC. Forecasts were created as hindcasts with historical data. Forecast start time was 9 UTC. Made with Natural Earth (https://www.naturalearthdata.com/).

Future work in this project includes developing road weather forecast products to meet the needs of different autonomous vehicles. Some autonomous vehicles might rely mostly on camera data, while others can have LiDARs and/or RADARs installed. Weather affects different instruments in different ways [16], so the forecasts should be tailored for each type of autonomous vehicle. The forecast products will use an estimate of the vehicles' ability to detect the surroundings in certain weather conditions together with road friction to give suggestions regarding lowering speed and whether a human should take over.

Precipitation nowcasts (concept better known as nowcasting) were produced by Pysteps, which is an open-source Python library [17]. The nowcasts were based on extrapolations of radar observations along the motion field estimated from past observations.

Nowcasting based on radar extrapolation provides better results than NWP-based models using short time ranges, that is, 0–6 h. Nowcasting models can produce reliable predictions of large-scale stratiform rainfall for up to 6 h and convective rainfall for up to the next 30–60 min. However, forecasting snowfall by using weather radars is still a challenging task. It is important to provide accurate information about precipitation for autonomous vehicles, as snowfall and heavy rainfall affect road conditions and the sensors' ability to observe the surroundings. In this project, we are developing a precipitation nowcasting web application to show results from a radar extrapolation algorithm in the Linnanmaa region in Oulu. The precipitation nowcast will be also given as input data for the road weather model to produce better road condition forecasts. Figure 5 shows an example of a precipitation nowcast for southern Finland.

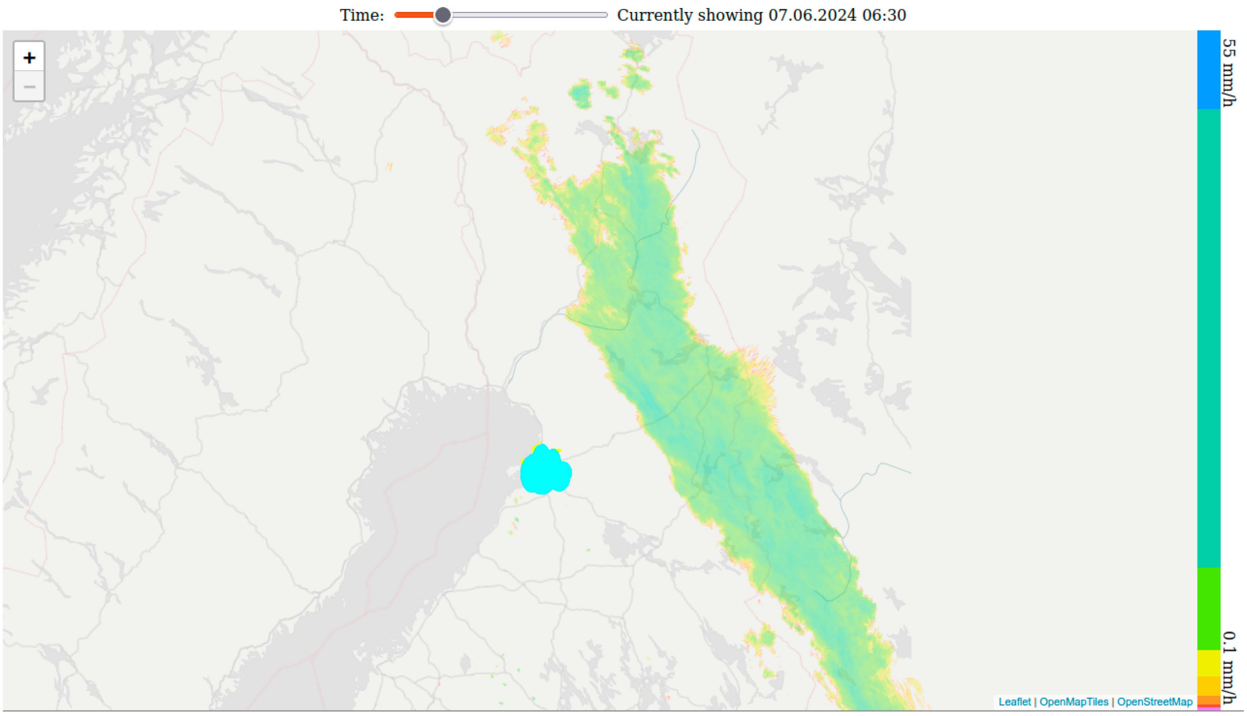

Figure 5. Example of precipitation nowcast for northern Finland. 6G Visible piloting area in turquoise.

5. Route Planning with Knowledge Modelling

Knowledge graphs (KGs) are knowledge structures that consist of multiple entities and their relations. They are used in many Artificial Intelligence (AI) systems [18]. Part of the 6G Visible project is to test knowledge modeling with knowledge graphs for automatic route planning [7]. Figure 6 shows a part of an ontology created in the project. Ontologies are semantic data models that define the base for knowledge graphs. In the project, real-time weather and forecast data will be integrated with KGs. In addition, traffic congestion and accident data will be used if possible. The knowledge modeling will be tested in driving scenarios where there are three alternative routes, and the system should automatically decide the best route. The routes start at a neighborhood to the south of Oulu city and end at the Oulu University campus to the north. The distance is about 20 km along the shortest route. The first route goes along the highway across the city, the second route goes through the city center, and the third route bypasses both the city and the highway. There is one road weather station on the city center route and one on the highway route. Currently, there are forecast points only along the highway route, but additional forecast points can be added to the other routes. The forecast points on the highway occur every 50 m.

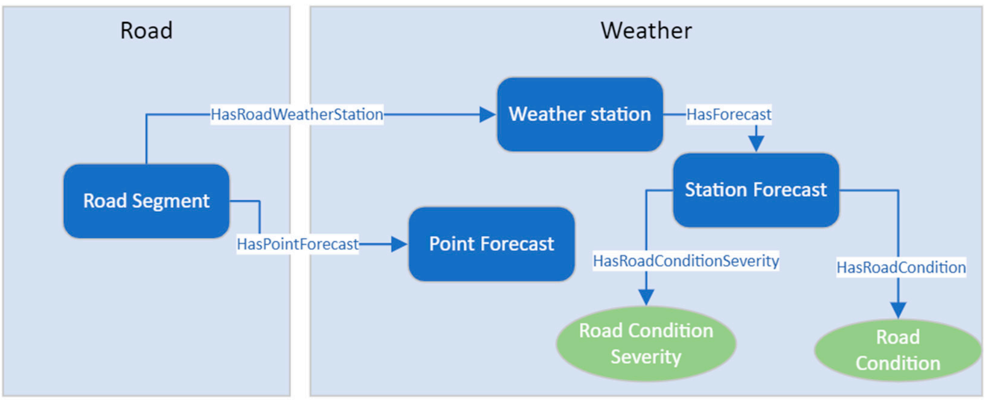

Figure 6. Part of knowledge ontology created in 6G Visible.

6. Predictive Modeling of Weather-Related Crashes

Vehicular crashes present inherent spatial and temporal trends, and the ability to explain crash risk patterns in southwestern Finland has been a key focus in the first stages of this 6G Visible task. The output of road crash modeling allows traffic authorities to implement targeted safety interventions when, and where, they are needed. By initially developing an explanatory model, we can better grasp the overall crash mechanism and its determinants, which lays the necessary foundation for the subsequent implementation of optimal route planning in terms of safety.

To build the model, crash data are obtained from the public data of Finnish Transport Infrastructure Agency for the years 2017–2021 inclusive, and the model uses forecasted MEPS data as explanatory variables. The timescale of the analysis is at the hourly resolution to account for the heterogeneity in road traffic density that exists throughout a given day. The spatial extent of the study includes the regions of Uusimaa and Varsinais-Suomi, and a grid consisting of smaller spatial cells based on fixed latitude and longitude increments is overlaid on top of these regions to explicitly define the spatial unit, as illustrated in Figure 7. A spatiotemporal join is then conducted to determine whether a crash has precisely occurred in each cell at a given hour.

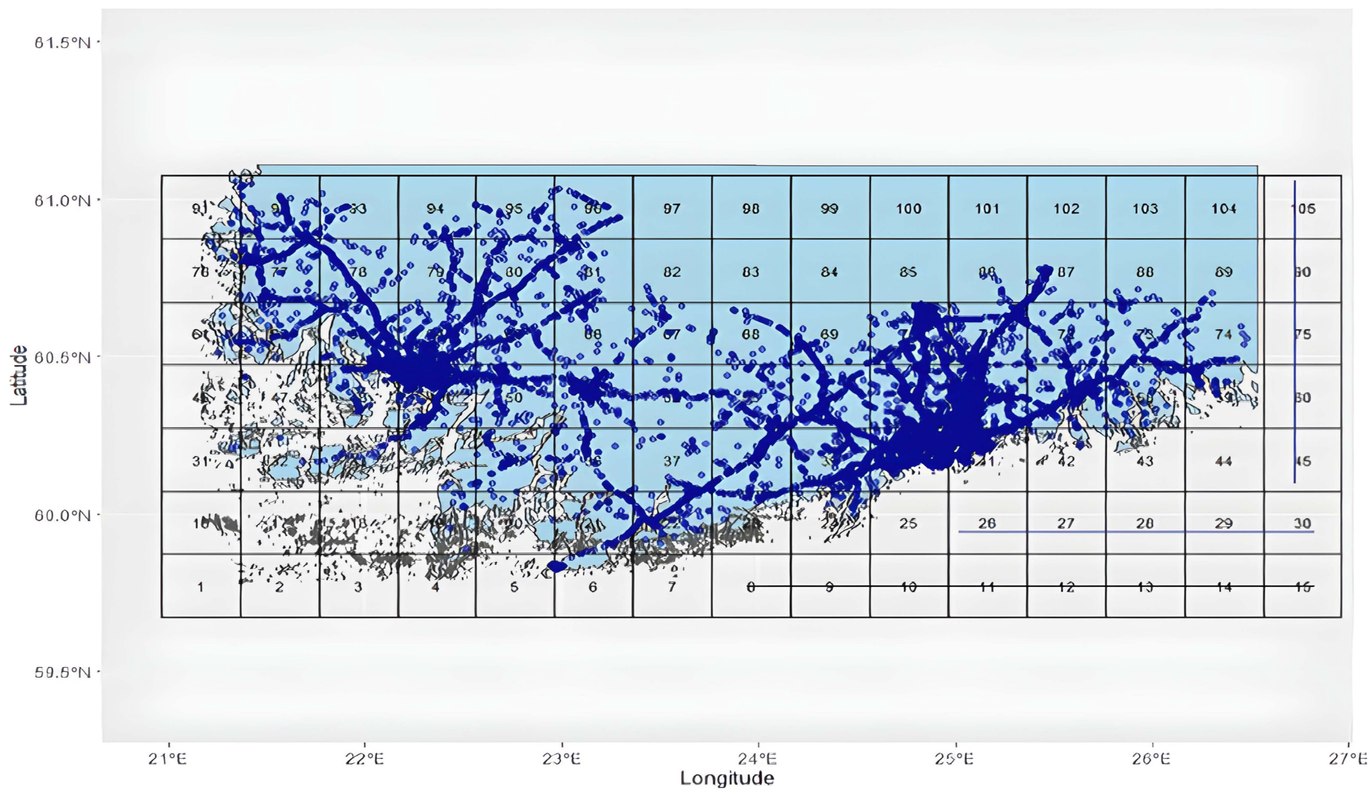

Figure 7. Defining the spatial unit: splitting the regions into grid cells, with crash point locations during the study duration shown as blue dots.

A spatiotemporal generalized additive model (GAM) with a logit link function was used to assign fitted probabilities of a car crash occurring at a combination of hourly and spatial units. GAMs are a powerful modeling tool for spatiotemporal analyses; they can uncover non-linear functional relationships between the predictor variables and the response, and their construction using a rich variety of different spline functions makes them flexible to capture trends in space and time [19]. The advantage of modeling probabilities is that they have a direct interpretation in terms of the crash risk level.

Henceforth, future directions involve extending this baseline explanatory model into one that can generate predictions within a 24 h window. A major task when developing this predictive model will involve assessing the accuracy of its predictions. Ultimately, we seek a collaboration in a data-driven decision theory framework between the road user and AI, whereby users can be informed about imminent weather-related driving risks on the road when planning a route between two points. To accomplish this, we will first aggregate the data into larger clusters that represent various combinations of meteorological parameters which are set to fixed and well-defined values to create an overall weather profile. Then, we will integrate the output of the predictive model into the knowledge graph construction, illustrating how the crash risk level depends on different temporal, spatial, and weather characteristics.

7. Results

Due to the early stage of the work, we have not been able to evaluate route planning with knowledge modeling, nor the route-planning-related precipitation nowcasting web application in its early development stage. Therefore, preliminary tests and evaluation work focus primarily on vehicle LiDAR and camera sensor sensitivity to harsh weather and communication measurements with alternative V2X radio systems, and are conducted in the test track environment. In the test track environment, LiDAR and camera imaging is not contaminated by the additional objects like vehicles and slush thrown by the vehicles, and the communication environment is protected from disturbing parallel transmission systems/activities. Therefore, the test track measurements are not completely equivalent to the measurements in the traffic environment, but are still perfect for our early-stage performance evaluation. The initial results concerning the data analysis and modeling of weather-related road crashes are also briefly presented.

7.1. Weather Sensitivity Analysis

LiDAR and a web camera were installed into the fixed position in the test track environment, regularly monitoring road area with two traffic signs. The web camera was kept in the same position all the time, while the LiDAR instrument was used for occasional on-board vehicle measurements as well. To ensure comparability of the measurements, the LiDAR instrument's position was carefully adjusted each time it was plugged in to the measurement system. As the monitoring system has been operative only since spring 2024, we have not yet achieved collective results from all kinds of difficult weather conditions. In Figure 8, a preliminary comparison of several different conditions is presented. On the top, there are parallel camera and LiDAR images with time stamps and collections of simultaneous measurement data from the road weather station, consisting of visibility, air (RWS temp) and road surface temperature, humidity, and wind speed and direction. The traffic sign visibility remains good in every camera image and LiDAR image, even in the snowy conditions observed on 29 April 2024. It is expected that when the density of snowing increases, it will affect the camera visibility immediately, but LiDAR might be able to achieve proper detection in certain snowing events when the water content of the snow remains low. This possibility will be evaluated in further measurements. Snow depth was not evaluated, as the measurement started when snow cover already existed. More measurements are required for a complete evaluation.

7.2. V2X Communications

The primary communication method between autonomous vehicles and the service core of route planning and road weather services, at a general level and especially for the pilots in the city of Oulu, is assumed to be commercial 4G/5G communication. In our communication tests at the Sodankylä test track, viewed in Figure 9, we also considered the possibility of delivering the service data with short-range vehicular networking (in our case ITS-G5 and C-V2X) along with 5G communication tests. Our objective was to evaluate the service operability in the case that short-range vehicular networking capabilities would be available in the public roads as well, but also to evaluate the performance of different V2X communication methods in our special use cases.

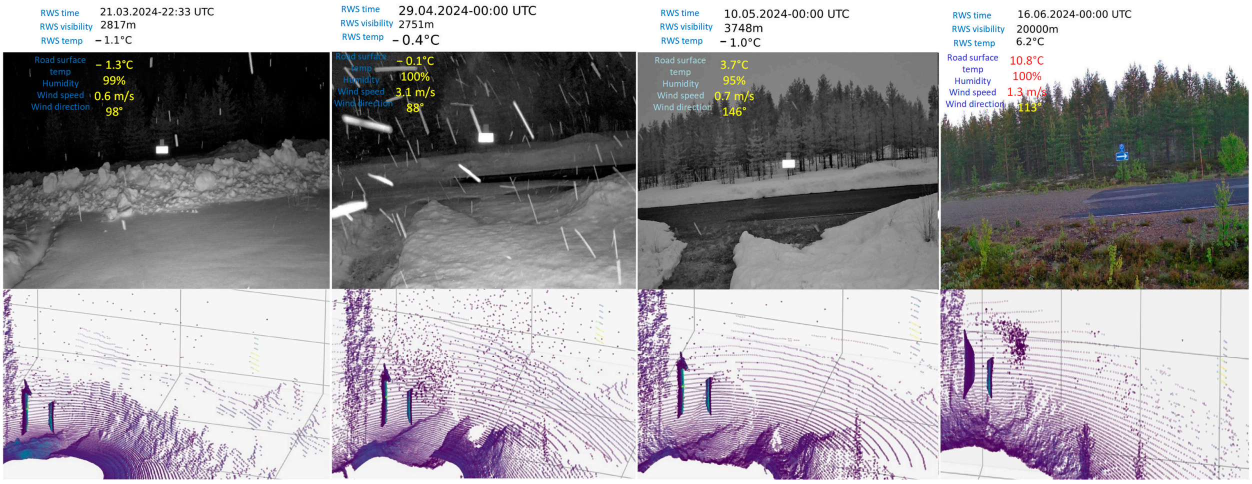

Figure 8. Preliminary comparison of LiDAR and camera images in different weather conditions.

Figure 9. Sod5G test track for development of intelligent traffic road weather services.

In ITS-G5 and C-V2X communication tests, we used the same procedure: an (autonomous) vehicle circled the test track and received a simple route and road weather data packet sent from transceiver located in RWS whenever it was in the range of the transceiver. Naturally, the procedure was the same with 5G measurements, but in this case, the communication range was not an issue, as the test network covered the test track entirely. The ranges of communication for both ITS-G5 and C-V2X tests are presented in Figure 10, consisting of "red dots" indicating single communication points where data packets were received, which form continuous red lines with many overlapping dots from consecutive test laps. There was no difference between the ranges of ITS-G5 and C-V2X. As stated earlier, the 5G network had complete coverage throughout the track. In ITS-G5 communication tests, we were able to measure both the communication throughput and the latency in separate tests. The throughput test consisted of four drive laps, presented as rows in Table 1 below. The latency test consisted of ten drive laps, presented in Table 2. In C-V2X communication tests, we could not capture the throughput of communication due to the black box nature of the C-V2X entity. Calculating just the number of transmitted packets and their size does not give a fair estimate of the throughput, as the exact size of the transmitted C-V2X packet is not known. Therefore, we were only able to measure the latency in C-V2X communication, presented in Table 3. Finally, 5G communication test results are shown in Table 4. Both throughput and latency are presented in this single table, as laps were not separated in this test (due to the continuous connectivity, separating laps was not relevant).

In our tests, ITS-G5 communication achieved an average of 4.24 Mbps throughput compared to 26.84 Mbps in 5G. In the 5G test network, the uplink bandwidth is limited to the scale of around tens of Mbps per user, explaining the relatively low round-trip throughput (compared to 5G theoretical capacity). The communication capacity is good enough to properly deliver route and road weather data even with ITS-G5, as well as with C-V2X (even if we could not define accurate throughput values). The latency tests presented a 5.49 ms average latency for ITS-G5, 29.11 ms latency for C-V2X, and 14.39 ms with 5G communication. The 5G test network suffers from the structure of our test network, the core being in VTT facilities at a 350 km single-direction distance and behind several routers, causing serious additional round-trip delays. Having a network core (or edge) in our test track facilities is expected to drop the latency down to the same level as ITS-G5.

Figure 10. ITS-G5 (**left**) and C-V2X (**right**) ranges in test measurements.

Table 1. Throughput in ITS-G5 tests, each representing one test drive lap.

Connection Points	Mean Throughput (Mbits/s)	Min 95% Confidence Interval	Max 95% Confidence Interval
43.0	4.378	4.304	4.453
82.0	4.1299	3.995	4.265
62.0	4.227	4.094	4.3597
90.0	4.284	4.213	4.3547

Table 2. Latency in ITS-G5 tests, each representing one test drive lap.

Connection Points	Mean Latency (ms)	Min 95% Confidence Interval	Max 95% Confidence Interval
130.0	4.874	4.771	4.977
585.0	6.294	3.439	9.149
584.0	4.8584	4.783	4.933
577.0	6.2674	3.562	8.973
586.0	4.896	4.799	4.993
578.0	7.937	3.687	12.187
642.0	4.771	4.743	4.800
607.0	4.772	4.737	4.808
104.0	4.723	4.675	4.772
790.0	4.767	4.740	4.793

Table 3. Latency in C-V2X tests, each representing one test drive lap.

Connection Points	Mean Latency (ms)	Min 95% Confidence Interval	Max 95% Confidence Interval
323.0	28.604	27.963	29.246
262.0	29.206	28.508	29.904
262.0	28.8543	28.321	29.388
223.0	28.840	28.112	29.568
233.0	28.990	28.258	29.722
213.0	29.013	28.255	29.771
407.0	29.896	29.322	30.470

Table 4. Throughput and latency in 5G communication tests measured in separate events, with all drive laps collected into a single measurement session.

Connection Points	Mean Throughput (Mbits/s)	Mean Latency (ms)	Min 95% Confidence Interval	Max 95% Confidence Interval
928	26.858	-	23.377	30.338
928	-	14.388	12.791	15.984

As stated above, the capacity of all evaluated networks was adequate for the service data delivery of route planning and road weather services. However, if we consider the idea of collecting continuous LiDAR and/or camera data from autonomous vehicles, generally, every communication system would fail to provide enough capacity. Even our relatively simple LiDAR imaging presented in Figure 2 requires an 18 Mbps uplink rate to collect from a vehicle or roadside.

And we are talking about just one vehicle. This kind of data collection from a traffic entity of multiple vehicles can only be realized by (1) packing/pre-processing the data in the vehicle before sending or (2) capturing only a burst of data, e.g., when passing a road weather station entity with high-capacity local networking.

7.3. Predictive Modelling of Weather-Related Crashes

So far, the model in its basic form has corroborated the well-established results from the existing literature [20]. Namely, the model establishes that precipitation falling as snow or sleet amplifies the risk of a car crash. Driving during the morning and late afternoon hours, as well as following the commuting flows into the urban areas of Helsinki and Turku, all increase the probability of an accident. In Figure 11, panel (b) precisely depicts this spatial pattern, since the highest fitted crash probability happens in the spatial cell containing the city of Helsinki. There is a clear distance decay effect, whereby the risk of an accident gradually decreases as one moves away from the city. The same is true for the zones around Turku. Additionally, panel (b) supports the information presented in panel (a), establishing that the fitted probabilities generated by the model have direct correspondence with the spatial crash concentration.

The proposed spatiotemporal GAM also acknowledges that crashes cannot be viewed as independent events, and the likelihood of a crash increases if another crash happened within the vicinity in the previous two hours. To aid in future predictions, temporal trends such as particular holiday periods will continue to be important in the model's development. Right now, the model indicates that the period spanning the Christmas holidays results in a decreased crash risk. Finally, it is essential to consider that driver unpreparedness in terms of unexpected weather conditions also adds an important safety risk.

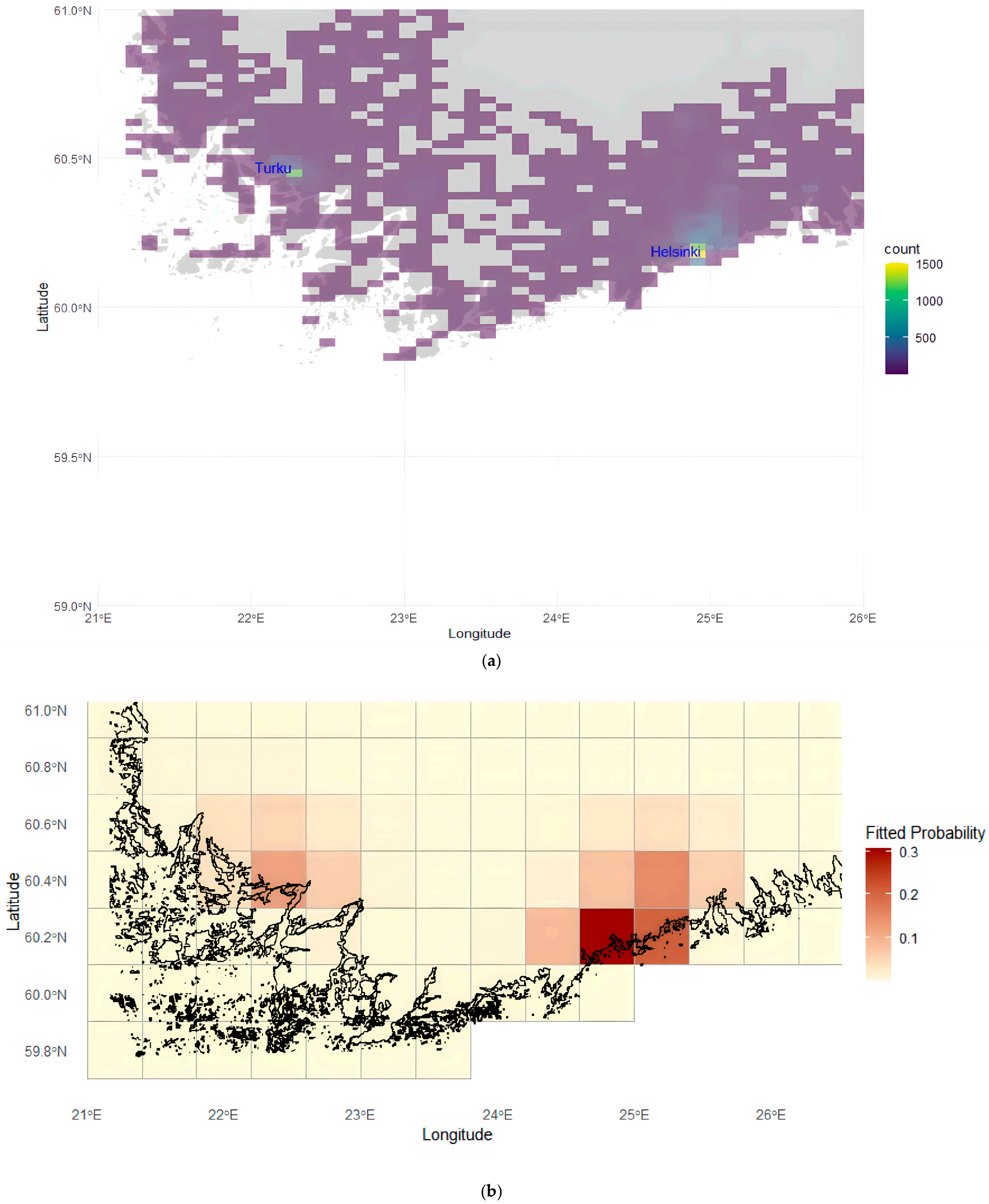

Figure 11. Understanding spatial crash trends in the study area. (**a**) Aggregated crash concentration in Uusimaa and Varsinais-Suomi for 2017–2021. (**b**) Cumulative effect of the fitted crash probabilities across all hours.

8. Conclusions

The 6G Visible project develops 6G-era service and architecture solutions utilizing autonomous and semi-autonomous driving. 6G Visible, being a distributed application with the main functionality of following up and predicting traffic situations with a broad set of sensors and providing vehicles with real-time steering guidance/commands, brings an important use case for the 6G solutions and services. Our approach, however, does not present a comprehensive package of services to be used/developed as a base of 6G architecture, but merely a practical set of services enabled by the innovations envisioned in 6G's pre-design. Our solutions developed in this project (until now and from now on) represent pre-6G infrastructure, which we intended to use as a building block and for practical visualizations of the design of the ultimate 6G infrastructure. 6G infrastructure is expected to be a collection of ambient, sophisticated networks in perfect mutual balance, or a traffic entity representing just one operation entity among multiple ones.

Finnish Meteorological Institute focuses on weather- and safety-related services for autonomous vehicles. The target is to tailor road weather services for the special needs of autonomous driving by adjusting weather warnings based on autonomous vehicle sensor sensitivity, especially LiDAR sensors, as well as by combining road weather forecasts and nowcasting short-term precipitation forecasts with specific route planning. Knowledge modeling based on weather and other parameters, as well as predictive modeling of weather-related crashes, will be essential to build a statistical background for these services. Intelligent traffic communication systems are evaluated as necessary data exchange platforms in our project pilot as well as in expected future deployment.

This paper provides the first-stage results of the project, which are to be supplemented in the following latter half of the project. Future work and results will consist of both practical use cases and development into pilot services, as well as practical ground proof material for the development of 6G-era service and architecture solutions, especially in the road traffic environment.

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References

1. Ross, P.E. Taxis Without Drivers-or Steering Wheels. *IEEE Spectrum* **2019**, *56*, 33–34. [CrossRef]
2. Automated Driving on Motorways (AUTOMOTO). In *FTIA publications 21/2021*; Finnish Transport Infrastructure Agency: Helsinki, Finland, 2021.
3. Marti, E.; de Miguel, M.A.; Garcia, F.; Perez, J. A Review of Sensor Technologies for Perception in Automated Driving. *IEEE Intell. Transp. Syst. Mag.* **2019**, *11*, 94–108. [CrossRef]
4. Xiang, C.; Feng, C.; Xie, X.; Shi, B.; Lu, H.; Lv, Y.; Yang, M.; Niu, Z. Multi-Sensor Fusion and Cooperative Perception for Autonomous Driving: A Review. *IEEE Intell. Transp. Syst. Mag.* **2023**, *15*, 36–58. [CrossRef]

5. Bilik, I. Comparative Analysis of Radar and Lidar Technologies for Automotive Applications. *IEEE Intell. Transp. Syst. Mag.* **2023**, *15*, 244–269. [CrossRef]
6. Ruotsalainen, L.; Renaudin, V.; Pei, L.; Piras, M.; Marais, J.; Cavalheri, E.; Kaasalainen, S. Toward Autonomous Driving in Arctic Areas. *IEEE Intell. Transp. Syst. Mag.* **2020**, *12*, 10–24. [CrossRef]
7. Karsisto, V.; Hippi, M.; Honkanen, H.; Myllykoski, H.; Mäenpää, K.; Pulkkinen, S.; Sanad, N.; Sebag, E.; Seppänen, P.; Sukuvaara, T.; et al. 6G VISIBLE. Intelligent Mobility for autonomous driving. In Proceedings of the 21st International Road Weather Conference, Amsterdam, The Netherlands, 11–13 June 2024; SIRWEC: Amsterdam, The Netherlands, 2024; Volume 11, p. 2024.
8. Business Finland "B5G and 6G", Bus. Finl. Natl. Strateg. Res. Innov. Agenda (SRIA). 2022. Available online: https://www.businessfinland.fi/490848/globalassets/business-finland---6g-bridge-program---b5g_and_6g_sria---2022.pdf (accessed on 18 June 2024).
9. Sukuvaara, T.; Mäenpää, K.; Stepanova, D.; Karsisto, V. Vehicular Networking Road Weather Information System Tailored for Arctic Winter Conditions. *Int. J. Commun. Netw. Inf. Secur. (IJCNIS)* **2020**, *12*, 281–288.
10. Ouster. *OS1 Mid-Range High-Resolution Imaging Lidar*; REV:06/2024; Ouster Inc.: San Francisco, CA, USA, 2024.
11. Saad, M.M.; Khan, M.T.R.; Shah, S.H.A.; Kim, D. Advancements in Vehicular Communication Technologies: C-V2X and NR-V2X Comparison. *IEEE Commun. Mag.* **2021**, *59*, 107–113. [CrossRef]
12. Ojanperä, T.; Scholliers, J.; Sukuvaara, T.; Yastrebova, A.; Miekkala, T.; Pyykönen, P.; Mäenpää, K.; Salkari, I.; Laakso, J.; Huuskonen, O.; et al. Piloting and Evaluation of 5G-Enabled Road Safety and Cybersecurity Services. In Proceedings of the EUCNC/6G Summit, Gothenburg, Sweden, 6–9 June 2023.
13. Karsisto, V. RoadSurf 1.1: Open-source road weather model library. *Geosci. Model Dev.* **2024**, *17*, 4837–4853. [CrossRef]
14. Frogner, I.L.; Andrae, U.L.F.; Bojarova, J.; Callado, A.; Escribà, P.A.U.; Feddersen, H.; Hally, A.; Kauhanen, J.; Randriamampianina, R.; Singleton, A.; et al. HarmonEPS-The HARMONIE ensemble prediction system. *Weather. Forecast.* **2019**, *34*, 1909–1937. [CrossRef]
15. Karsisto, V.; Horttanainen, M. Sky View Factor and screening impacts on the forecast accuracy of road surface temperatures in Finland. *J. Appl. Meteorol. Climatol.* **2023**, *62*, 121–138. [CrossRef]
16. Vargas, J.; Alsweiss, S.; Toker, O.; Razdan, R.; Santos, J. An overview of autonomous vehicles sensors and their vulnerability to weather conditions. *Sensors* **2021**, *21*, 5397. [CrossRef] [PubMed]
17. Pulkkinen, S.; Nerini, D.; Pérez Hortal, A.A.; Velasco-Forero, C.; Seed, A.; Germann, U.; Foresti, L. Pysteps: An open-source Python library for probabilistic precipitation nowcasting (v1.0). *Geosci. Model Dev.* **2019**, *12*, 4185–4219. [CrossRef]
18. Chen, Z.; Wang, Y.; Zhao, B.; Cheng, J.; Zhao, X.; Duan, Z. Knowledge Graph Completion: A Review. *IEEE Access* **2020**, *8*, 192435–192456. [CrossRef]
19. Feng, C. Spatial-temporal generalized additive model for modeling COVID-19 mortality risk in Toronto, Canada. *Spat. Stat.* **2022**, *49*, 100526. Available online: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8257405/ (accessed on 18 June 2024). [CrossRef] [PubMed]
20. Becker, N.; Rust, H.W.; Ulbrich, U. Weather impacts on various types of road crashes: A quantitative analysis using generalized additive models. *Eur. Transp. Res. Rev.* **2022**, *14*, 37. [CrossRef]