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REVIEW

The use of vehicle-based observations in weather prediction and decision support

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Abstract

Vehicle-based mobile observations are taken across the world every day by operational and research meteorological organizations, public transportation agencies, and private car manufacturers. Whether directly weather-related (e.g., air temperature) or not (e.g., wiper speed), the coverage and frequency of these observations holds the promise of filling in gaps between fixed observing stations and greatly improving situational awareness and weather forecasting, from road surface condition-specific applications and winter road maintenance to urban and street-level numerical weather prediction and beyond. However, in order to take advantage of these observations, the weather, water, and climate enterprise must work together with the transportation enterprise across academic, public, and private sectors to provide a mechanism for obtaining these data, so that the benefits of using these unconventional observations may be realized.

KEYWORDS

automated vehicles, connected vehicles, crowdsourcing, road weather, unconventional observations

1 | INTRODUCTION

Every day, millions of commercial and personal vehicles are driven across the world. Each one of these vehicles, if properly connected to the infrastructure, possesses the potential to provide high temporal and spatial resolution meteorological observations. From externally mounted gold standard instrumentation, to modern connected vehicle (CV)-enabled air temperature observations, to the speed of windshield wipers or engagement of traction and stability controls, potentially billions of weather-related data points could be made available for a wide variety of applications.

A CV is one that is able to communicate between other CVs and the fixed infrastructure to exchange information relevant to the safe and efficient operation of the vehicle (Figure 1). Such a vehicle may become a weather sensor (Drobot et al., 2010) through traditional observations such as air temperature and unconventional observations such as wiper speed (Figure 2), or through the mounting of an external weather sensor. These data, already available on many vehicles on the road today, hold the promise for improved weather prediction, transportation safety, and mobility (Mahoney & O'Sullivan, 2013). While some observations in Figure 2 such as outside air temperature and barometric pressure are straightforward to incorporate into a variety of applications, others take some processing. For example, wiper status or speed can be used for determining precipitation intensity (Bartos et al., 2019; Siems-Anderson et al., 2017). Braking and stability controls (such as Anti-lock Braking System, Traction

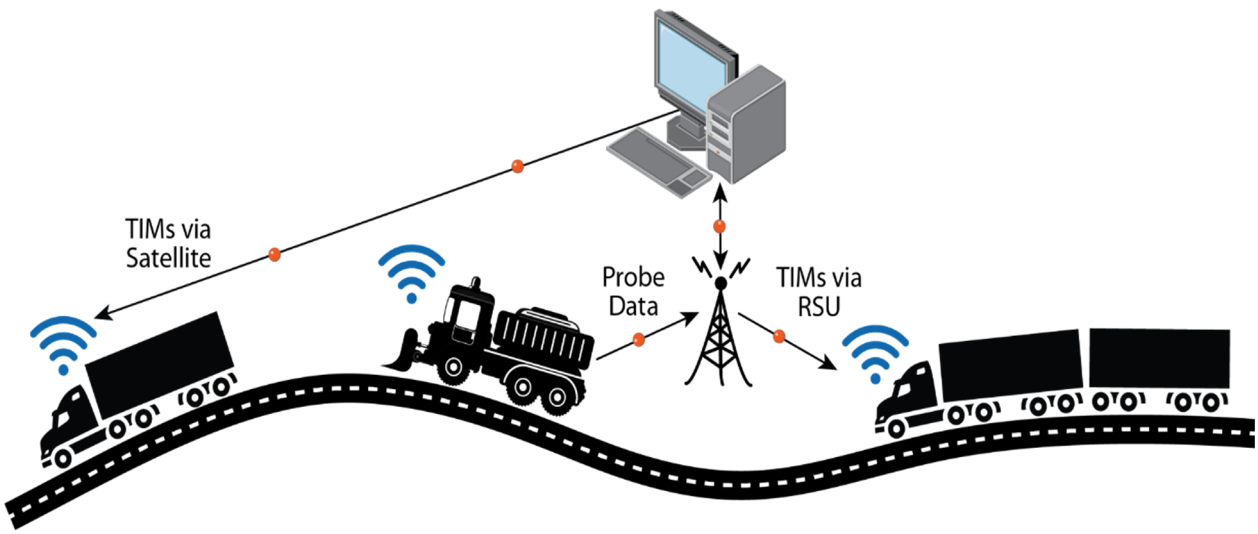

FIGURE 1 An illustration of connected vehicle (CV) communications from the Wyoming Connected Vehicle Pilot Deployment (Siems-Anderson et al., 2017). This illustrates the transmission of Probe Data from a CV to the infrastructure, as well as Traveler Information Messages (TIMs) sent from the infrastructure to another CV via Road Side Unit (RSU) and a non-CV via Satellite.

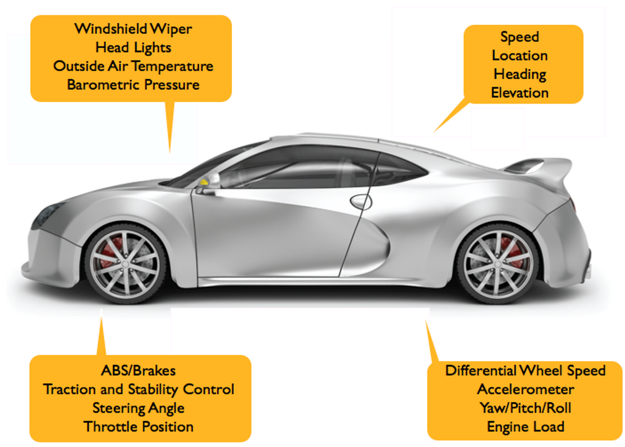

FIGURE 2 Illustration of a vehicle as a weather-observing platform.

and Stability Control) and differential wheel speed can give information about the slickness of the pavement (Zachrisson & Hägg, 2023). Speed and location are useful metadata and for quality control (Bell et al., 2022).

This paper discusses the historical use of observations from vehicles, presents a wide variety of weather applications currently taking advantage of these observations, and touches on the public policy considerations of this unique source of weather data.

2 | HISTORY OF MOBILE OBSERVATION USE

The concept of mobile observations in atmospheric science research and operations has existed for many years. From deploying temporary surface observing stations for field experiments to the mobile mesonet that was a part of the Verification of the Origins of Rotation in Tornadoes Experiment (VORTEX; Rasmussen et al., 1994), atmospheric research has necessitated observations to be taken in between the operational infrastructure. However, these deployments are temporary, lasting only as long as the field campaign has been scheduled. CV technology, on the other hand, provides infrastructure-based communications with vehicles to provide observations as often as a vehicle takes to the road.

There are a number of ways these data may be accessed. The most straightforward, which works with a wide variety of vehicles, is the addition of an external weather instrument that connects to a database via laptop, bluetooth, or cellular network (Chapman et al., 2010). Examples include Automatic Vehicle Location (AVL) systems deployed by a number of state Departments of Transportation (DOTs) in the United States (Schneider et al., 2017) and by field programs (Anderson et al., 2012). Instruments such as these turn vehicles into mobile weather-observing stations for a variety of applications and are provided by a number of manufacturers around the world.

The continuing adoption of CV technology provides another method of connecting with and collecting observations from vehicle-mounted sensors. It also gives a method of access to the Controller Area Network (CAN)-bus of a vehicle, where data such as vehicle position, speed, air temperature, and wiper speed may be obtained. Most often considered in the context of safety applications (Thota et al., 2020), observations from the CAN-bus can also be applied to weather (Mercelis et al., 2020).

While observations like air temperature are straightforward to use (Bell et al., 2022), other vehicle data may also be converted into weather observations. For example, the speed of the windshield wipers provides a measure of precipitation intensity, while the engagement of the Anti-Lock Braking System (ABS) or traction control gives an estimate of friction on the road surface. Algorithms to convert vehicle observations into inferences about current weather conditions are the basis for such applications as the Pikalert® system (Siems-Anderson et al., 2019) and a short-term alarm system developed at Météo-France (Coudert, 2017). Data from the CAN-bus may be kept proprietary by the Original Equipment Manufacturer (OEM) or collected for agency use by transportation authorities (Chapman et al., 2013). A number of private companies provide observations from CVs to customers as well. Most recently, the advances in Automated (or Self-Driving) Vehicles (AVs) provide additional opportunities for on-the-road inferences, such as through the optical camera (Goberville et al., 2023). The Section 4 provides an overview of some of these applications.

3 | DATA QUALITY CONCERNS AND CHALLENGES

With an unregulated dataset of opportunity such as CVs, a wide variety of issues must be recognized and addressed in order to incorporate these data into the many weather-related applications that may benefit from them.

Firstly, vehicle data are available from a number of disparate sources, distributed nonuniformly both through space and time. This makes the collection of data difficult and must be taken into account when applying applications, particularly when considering urban areas (Siems-Anderson et al., 2020). Connectivity at a location may also lead to latent data, which can make the data of little use to real-time or semi-real time applications (ITS JPO, 2021; Siems-Anderson et al., 2019).

Bell et al. (2015) and Bell et al. (2022) discuss in detail issues surrounding metadata, which is often not available in part or in full compared with gold standard weather sensors. Additionally, if metadata are available for an observation, they may be incorrect and require quality control themselves. Examples include location, accurate time stamp, and information about the type of sensor and its location, for example, if an ambient air temperature sensor is located in an outside mirror or on the front of the vehicle. Other pertinent information useful for quality control, such as vehicle identification that can be used to determine if an observation is changing through time too little or too much, is often removed for privacy reasons (Siems-Anderson et al., 2019).

Finally, traditional quality control techniques may not be relevant to, or as easily applicable to, the moving platform. Madaus and Mass (2017) and Hintz et al. (2019) looked at this from the approach of collecting barometric pressure observations from smartphones, which will relocate through time with their owner. Both emphasized the use of the observation location in identifying nearby reference observations for comparison, underscoring the importance of accurate position metadata. Movement is also important not just in applying quality control, but in obtaining quality observations. For Hintz et al. (2019), the use of pressure tendency rather than absolute values from non-moving smartphones provided an avenue for reducing observation error. In the case of the vehicle, observations such as ambient air temperature increase in accuracy when the vehicle is moving and proper mixing of the air around the vehicle can occur, rather than a temperature from a vehicle that is idling in traffic or parked in a garage (Anderson et al., 2012; Siems-Anderson et al., 2023).

Although there are many challenges to quality controlling mobile observations, systems designed to ingest such data do include quality control procedures. For example, Pikalert (Siems-Anderson et al., 2019) employs a set of quality checking algorithms that include the following:

- Data Filtering Test: Allows the user to filter out data that may not work well in the system. For example, observations where the vehicle speed is zero.
- Sensor Range Test: Removes data that does not fall in the expected range of the sensor, used when such metadata are available.
- Spatial Test: Compares atmospheric observations (e.g., ambient air temperature) to other nearby stations using a Boolean or interquartile range method.
- Model Analysis Test: Compares atmospheric observations against nearby gridded analyses. Useful in areas without many infrastructure-based weather sensors.
- Climate Range Test: Compares atmospheric observations against climatic extremes within a tolerance allowing for records.
- Persistence Test: If a vehicle identification is available (e.g., a public agency fleet vehicle), it determines whether a sensor observation expected to change is remaining constant.
- Step Test: If a vehicle identification is available, it detects unreasonably large changes in sensor values over a user-defined length of time.
- Neighboring Vehicle Test: Compares the vehicle observations to other nearby vehicles.
- Combined Algorithm Test: Combines the results of the above tests to give a final confidence value between

0 and 1, from which observations may be filtered from further use in the system.

Bell et al. (2022) employed a quality control process for their vehicle-based dataset, which did not take advantage of spatial consistency tests due to the sparsity of data in space and time. Data were filtered if relevant metadata were not available, removing approximately half of the original dataset. They then tested if the air temperature observation was reasonable compared to climatological ranges. After this, data were run through a Stuck Instrument Test to determine if observations were changing through time as expected. Finally, they developed a novel process for quality controlling the GPS location associated with the observations, determining whether or not distance between observations was reasonable. For these last two tests, a vehicle identification was required.

For applications such as those discussed in the following section, it is critical that the user of mobile observations keeps in mind the above challenges and takes the necessary measures to employ quality control to the mobile datasets.

4 | APPLICATIONS

Traditionally relegated to the field of surface transportation weather, mobile observations have improved winter weather maintenance and traveler information in a number of different applications. Additionally, other areas such as urban heat island research and numerical weather prediction (NWP) have begun harnessing this rich source of data.

4.1 | Winter maintenance decision support

Perhaps the most common use of mobile observations is in the winter weather maintenance decision support space. One of the flagship systems in this category is the Maintenance Decision Support System (MDSS, Pisano et al., 2006). In 1999, the U.S. Federal Highway Administration (FHWA) began studying the lack of integration of weather information into transportation operations with their study, Surface Transportation Weather Decision Support Requirements (STWDSR; Mitretek Systems, 1999). As a result, FHWA assembled a team of U.S. national laboratories alongside a stakeholder group of state DOTs, private sector weather providers, and academic institutions. Based on stakeholder feedback, the national laboratories (i.e., U.S. Army Cold Regions Research and Engineering Laboratory, National Center for Atmospheric Research, Massachusetts Institute of Technology – Lincoln Laboratory, National Oceanic and Atmospheric Administration [NOAA] Forecast Systems Laboratory, and NOAA National Severe Storms Laboratory) created the MDSS federal prototype (Pisano et al., 2005). The system ingests and combines NWP outputs (10 different models in the case of the federal prototype) into the Road Weather Forecast System (RWFS). In addition to model data, the RWFS also uses surface observations from airports and Road Weather Information System (RWIS; Manfredi et al., 2005) stations along the roadway. Once the RWFS blended forecast is processed, the Road Condition and Treatment Module (RCTM) employs this forecast alongside the Model of the Environment and Temperature of Roads (METRo, Crevier & Delage, 2001). METRo closely resembles Sass's (1992), Sass's (1997) physical model of road surface energy balance and produces forecasts of road surface temperature and condition based on input atmospheric models (e.g., RWFS). The road surface conditions specifically forecast by RCTM include snow accumulation, road and bridge frost probability, blowing snow probability, and chemical concentration and dilution, in addition to the road surface temperature. Within RCTM, this forecast then integrates with DOT rules of practice for anti-icing and deicing maintenance efforts to output a route-specific forecast of weather, road conditions, and treatment recommendations. An example of treatment recommendations from the original federal prototype can be seen in Figure 3. MDSS represents a successful technology transfer between a federally funded and academically developed system to the private sector, which continues to work with state DOTs and other entities to develop MDSS through the Pooled Fund Study, which has been ongoing for over 20 years (Pisano et al., 2006).

Despite its successful deployment, it was not until integration into the Pikalert System (Siems-Anderson et al., 2019) that mobile observations were used in MDSS. CV data are ingested by Pikalert and are used to forward error correct the RWFS. As shown in Figure 4, in forward error correction an observation (in this case, from CV data) is used to improve the 0 hour forecast and the subsequent 3+ hours forecast, leading to improvements in the near-term atmospheric and road surface condition forecasts. This in turn improve the ability of MDSS to recommend treatments along maintenance routes. Additionally, members of the MDSS Pooled Fund Study are working to integrate AVL data, which includes plowing strategies and spreader information (Lee & Nelson, 2018).

Other such systems have been developed as well. The WiRMA project is taking an Internet of Things (IoT) approach to integrating vehicle-based sensors, road

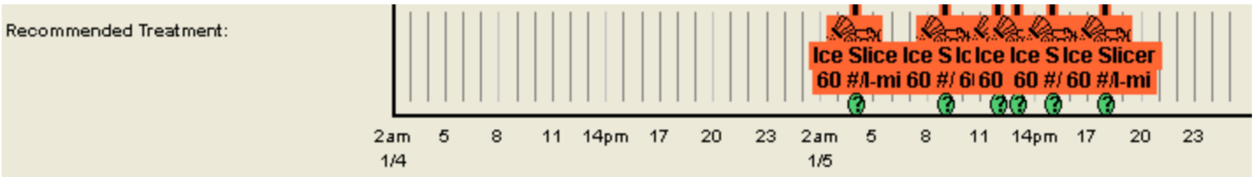

FIGURE 3 Example treatment recommendations from the federal prototype MDSS. In this example, plowing is recommended on this route at 4 am, 9 am, 12 pm, 1 pm, 3 pm, and 6 pm on January 5 with application of the chemical Ice Slicer at 60 pounds per lane mile (17 kg per lane km).

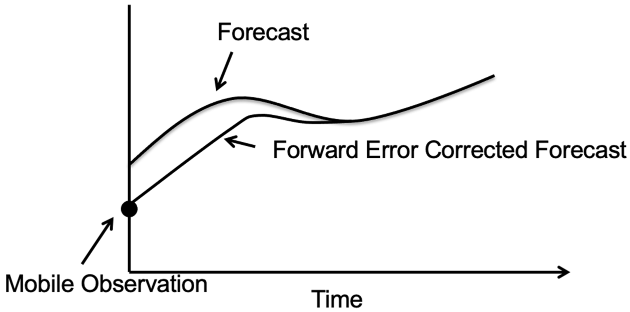

FIGURE 4 Illustration of forward error correction being applied to an RWFS forecast for air temperature. The original forecast is on the top, but a CV observation has indicated the analysis time (forecast hour 0) is too warm. The 0 h forecast has been matched to the CV observation, and subsequent blending through the first 6 h of the forecast has occurred to correct to the CV observation.

infrastructure data, and fixed weather sensors such as RWIS stations to support maintenance decisions (Karsisto & Lovén, 2019; Lusikka et al., 2019). Slovakia has also developed and implemented an MDSS (Benko, 2012). Many private companies have implemented MDSS, either based on the federal prototype or by developing their own in-house proprietary version (Vaisala, 2010), in addition to those participating in the MDSS Pooled Fund Study. In Belgium, a fleet of vehicles was equipped with external weather sensors to monitor conditions and a machine learning approach taken to retrieve data that were integrated into a short-term road weather forecast model (Bogaerts et al., 2022).

4.2 | Traveler safety and information

Along with maintenance decision support useful to transportation agencies, mobile observations provide useful information for the traveling public. With 90% of travelers in the United States desiring better in-cab weather information (Drobot et al., 2014), vehicles have the potential to provide their driver with up-to-date inferences of current and forecast conditions, particularly through the use of CV communications, which allows for the sharing of information between vehicles and data processing centers in the infrastructure (ITS JPO, 2020).

The Pikalert system (Siems-Anderson et al., 2019) represents one such traveler information system. Observations from the vehicle, including air temperature, windshield wiper speed, braking status, and vehicle speed, are provided to the system's Vehicle Data Translator (VDT) either anonymously from the public or tagged with a vehicle identification in the case of public agency fleet vehicles. These data are then quality-checked against infrastructure-based weather observations, surrounding vehicles, and in the case of public identified vehicles, past observations. More information about these quality checking tests can be found in Section 3 and Siems-Anderson et al. (2019).

The quality-checked vehicle observations are then processed through the Road Weather Hazard (RWH) module, which combines them with traditional, ancillary weather observations from the infrastructure to produce inferences of precipitation, road surface condition, visibility, and high wind blowover risk (Figure 5). Vehicle observations may also be used to forward error correct the forecast component of the system. Such data may be used to inform traveler applications, such as the Wyoming DOT's use of Pikalert assessments to assist their Traffic Management Center (TMC) operators in updating their Wyoming Travel Information (WTI) map, part of a larger CV deployment (ITS JPO, 2021; Siems-Anderson et al., 2017).

Not all traveler safety and information applications involve direct weather inferences. The Pikalert system includes a travel time application that takes weather forecasts into account when producing predictions of travel times. Vehicle speeds observed in various weather conditions served as the basis for the application's machine learning algorithm. And while not directly weather-related, crash avoidance applications of CV communications (ITS JPO, 2020) benefit from information on weather conditions to inform them. For example, stopping distance increases in reduced friction environments (Juga et al., 2013), affecting the distance at which a forward collision warning must be sounded.

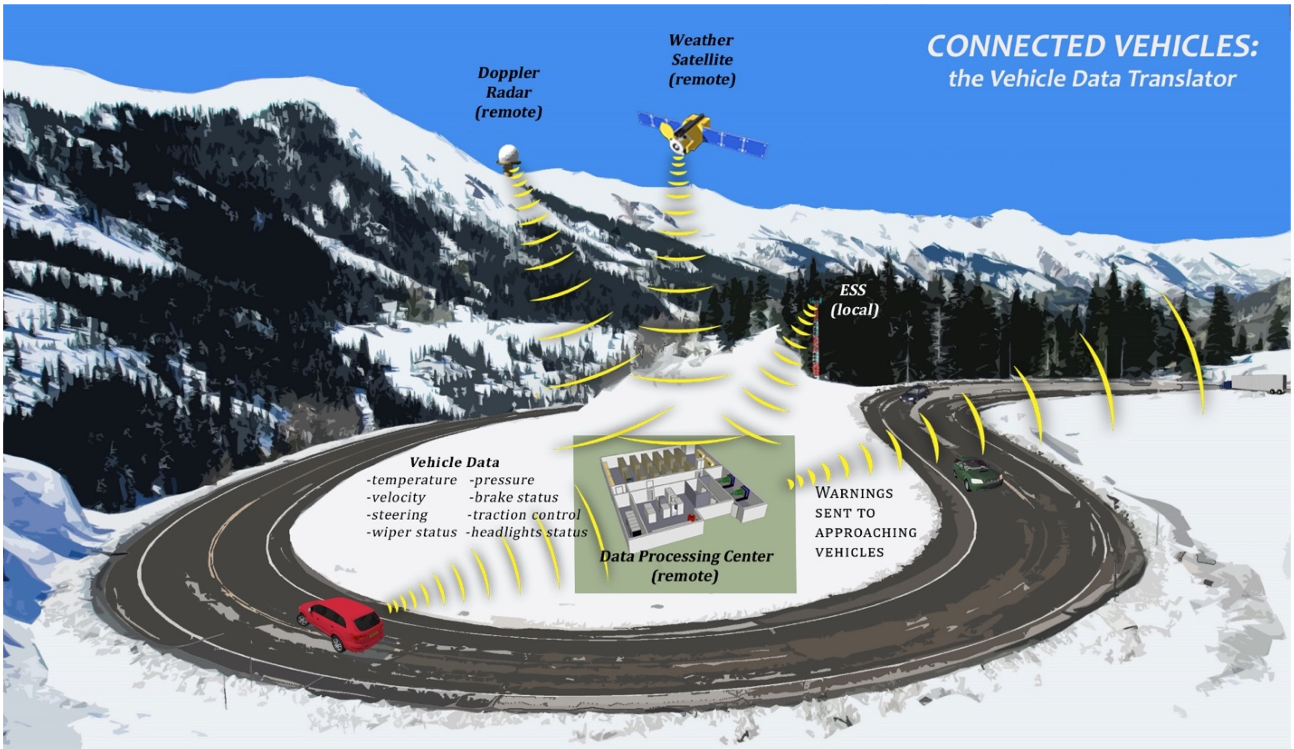

FIGURE 5 Illustration of the Pikalert system obtaining CV data, processing observations, and returning weather inferences to CVs.

4.3 | Other meteorological applications

While the bulk of work has been devoted to winter weather, the community has also been involved in developing non-winter weather applications. The Arizona DOT has implemented a dust detection system along their highways (AZDOT, 2021) using radar. While not directly involving mobile observations, certainly data from CV-enabled vehicles could provide complementary information regarding speed and vehicle behavior.

Urban modeling is also a major area of research and development in the mobile observation space. Knight et al. (2010) leveraged crowd-sourced observations from drivers manually recording the air temperature displayed on their vehicles. Marquès et al. (2022) used opportunistic observations of air temperature from cars in the cities of Rennes and Dijon to assist in the mapping of the urban heat island effect in support of urban planning decisions. Lopes et al. (2021) used connected vehicle air temperature observation mapping in Brazil to study the climate implications of reduced travel during the COVID-19 pandemic shutdowns.

Another relevant area of research in mobile observations takes advantage of crowd sourcing (Muller et al., 2015). Bell et al. (2022) describe a Met Office proof-of-concept pilot study in which air temperature observations were collected from vehicles via broadcast to a user's smartphone. They emphasized the need for high quality metadata and quality control while acknowledging the potential usefulness of the high temporal and spatial resolution data in NWP. Walker et al. (2022) created a machine learning flood severity index that used both remotely sensed vehicle speeds and crowd-sourced flooding reports from Waze in conjunction with traditional hydrometeorological data. These crowd-sourced observations provided observations not only of flooded roads, but also of flooding impacts such as road closures that significantly impact mobility during major events.

Work has also been done in assimilating vehicle-based observations into NWP models. Siems-Anderson et al. (2020) used the Pikalert system as a quasi-Observing System Simulation Experiment (OSSE) to examine the impacts of mobile-based inferences on road segments on Weather Research and Forecasting (WRF, Skamarock et al., 2008) model forecasts. While assimilating using a nudging method yielded mixed results in WRF forecast performance, the use of windshield wiper speed data through forward error correction in post-processing yielded large improvements in probability of precipitation (PoP) and quantitative precipitation forecasts (QPF; Figure 6). Bell et al. (2022) also explored the utility of vehicle-based air temperature observations in NWP as a source of high temporal and spatial resolution data assimilation for convection-permitting models.

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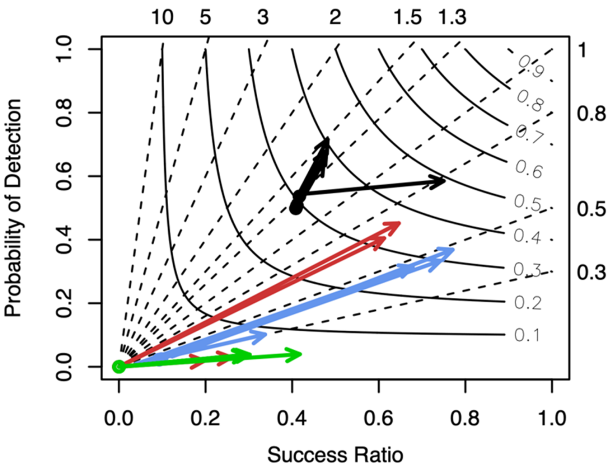

FIGURE 6 Performance diagram of contingency statistics results of using wiper status to forward error correct QPF from the RWFS. The arrow base is the original forecast verification and the tip points to the improvement seen using wiper status. Success ratio (1 – False Alarm Ratio) is on the x-axis and Probability of Detection (POD) is on the y-axis. Critical Success Index (CSI) is represented by curved solid lines and Bias by dashed diagonal lines. Each arrow is a different lead time from 0 to 6 h at thresholds of 0.01 mm (black), 1 mm (blue), 2 mm (red), and 5 mm (green). A circle indicates little to no change (Siems-Anderson et al., 2020).

4.4 | Automated vehicles

Alongside CVs, automated vehicles (AVs) hold the potential for providing vehicle-relevant weather observations that could be harnessed by the larger community. Goberville et al. (2023) use the vehicle's roof-mounted camera to provide an estimate of roadway snow cover. Rothenberg (2023) discuss leveraging their AV's perception systems to assess foggy conditions in San Francisco. The Mcity testbed in Ann Arbor, Michigan takes advantage of their location's high frequency of precipitation, both rain and snow, to collect data from and test vehicles in a variety of weather conditions (Dong et al., 2019). The necessity for on-vehicle weather observations becomes apparent in the issues of sensor degradation (Goberville et al., 2020; Kutila et al., 2018) and the highly variable nature of road weather conditions that render it difficult to fill in the gaps between infrastructure-based sensors (Siems-Anderson et al., 2023). Complementarily, new perception systems such as cameras, radar, and lidar on AVs could provide information on precipitation, road surface condition, and other weather impacts to the wider weather research and forecasting community.

While work in this space is relatively new, AVs represent another opportunity for the weather, water, and climate enterprise to leverage high fidelity vehicle-based observations for a wide variety of applications.

5 | POLICY

A wide range of research has been conducted and useful decision support and forecasting applications developed based on mobile observations. However, there are a number of public policy hurdles that must be navigated in the effort to widely deploy technology that would enable use of the potentially billions of observations from vehicles on the road every day.

In the United States, CV technology deployment was initially inhibited by the Federal Communications Commission (FCC) ruling on opening up the 5.9 GHz band, originally designated for CV safety applications, to private wireless commercial development (FCC, 2020). However, a recent decision saw the FCC approving a joint waiver that allows 14 states, automakers, and other stakeholders in the United States to use the 5.9 GHz spectrum in the pursuit of CV, specifically Cellular Vehicle-to-Everything (C-V2X) technology (FCC, 2023).

Due to the nature of using the vehicle as an observing platform, specifically that most vehicles are privately owned, data sharing policy must be carefully considered. Walker et al. (2020) explore this in relation to AVs, but data sharing and privacy considerations have been and will remain an important part of policy for both CV and AV data collection moving forward, particularly as up until this point data collection has remained in academic settings or been obtained from public fleet vehicles, although this is beginning to change (Zachrisson et al., 2023). Alongside personal privacy, OEMs often do not share such data, holding them as proprietary, as these data are commercially lucrative to services their specific vehicles provide their drivers and serve as marketing tools.

In addition to policy considerations surrounding the collection of mobile vehicle data, it is important to consider the use of such data in weather applications. As noted by Siems-Anderson et al. (2019) and Bell et al. (2022), quality control is critical for these observations to provide useful data to NWP and other applications. Additionally, the sheer vastness of data available will require a big data solution to collecting, quality controlling, and utilizing these observations. For consistent adaptation of high quality mobile observations, quality control policy and best practices should be established.

As more and more CVs come online, these cross-industry discussions will become ever more critical. The American Meteorological Society (AMS) Washington Forum (AMS, 2023a), which brings together public, private, and academic sectors to discuss public policy issues across the weather, water, and climate enterprise, is an example of a venue where CV and AV policy may be discussed between transportation and weather sectors. During the 2023 meeting, weather and transportation experts from the private, public, and academic sectors came together to discuss the challenges of implementing AV technology in adverse weather conditions and potential solutions. All panelists agreed that cross sector collaboration, both public/private and weather/transportation, was critical to address these challenges. Public adoption of the technology was also discussed when an audience member questioned whether or not AV technology was even necessary, to which a panelist responded with the potential life-saving crash avoidance that could be achieved from successful implementation. There was also discussion between the public and private sectors of which weather observations, and in what fidelity, are needed from government agencies and other weather providers, with a private sector AV panelist describing how they were not even sure where to start with weather. Further information about the session, including a recording, is available at AMS (2023b).

Additionally, the AMS will be hosting a meeting titled Automated Vehicles and Meteorology Summit, to be held on June 25–27, 2024 in Ann Arbor, Michigan, USA (AMS, 2023c). The goal of this meeting is to bring together scientists, engineers, policymakers, industry specialists, and practitioners from across the public, private, and academic sectors to discuss challenges and solutions related to the operation of AVs in adverse weather conditions. However, weather remains a small presence at transportation conferences and in CV and AV implementation policy. The meteorological community must continue to reach out to and interface with the transportation community in order to effectively use CV-based observations.

6 | THE PROMISE OF MOBILE OBSERVATIONS

Vehicle-based observations provide high temporal and spatial resolution observations across the roadways in many countries around the world, yet these unconventional observations remain mostly in the purview of road weather-related applications and have not yet seen wider adoption by the meteorological community. While progress is being made in new areas like NWP data assimilation, climate mapping, and urban heat island observing and modeling, these data are often difficult to obtain, quality control, and use. To address these issues, several research and policy questions remain to be answered. Among these are:

- How to establish quality standards for a dataset that is nonuniform in spatial and temporal distribution and lacking in metadata and routine maintenance.
- How should agencies and entities balance quality control with data privacy concerns.
- How to make these data available to the community, to hasten development of applications for their use in both weather and transportation.

Moving forward, transportation agencies are continuing to implement CV and AV communications and infrastructure in their jurisdictions and across their public fleets. OEMs are developing and using a variety of communication mechanisms to provide value to their customers. Working through data sharing platforms such as the Weather Data Environment (FHWA, 2023) or the Met Office's Weather Observation Website (WOW; O'Hara et al., 2023) are potential ways mobile observations can be quality checked and made available for forecasting and research. Ultimately, public policy will be needed to guide the partnerships required to make these unconventional data available to the weather, water, and climate enterprise as a whole.

AUTHOR CONTRIBUTIONS

Amanda R. Siems-Anderson: Conceptualization (lead); writing – original draft (lead).

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CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest to declare within the manuscript.

DATA AVAILABILITY STATEMENT

Data sharing not applicable - no new data generated.

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REFERENCES

AMS. (2023a) The 2023 AMS Washington Forum. Available from: https://www.ametsoc.org/index.cfm/ams/meetings-events/ams-meetings/2023-ams-washington-forum/ [Accessed 17th April 2023].

AMS. (2023b) *Session 6: weather, automated vehicles, and society*. Washington, DC, USA: AMS Washington Forum, AMS. Available from: https://ams.confex.com/ams/AMSAWF23/meetingapp.cgi/Session/64908

AMS. (2023c) Automated vehicles & meteorology summit. Available from: https://www.ametsoc.org/index.cfm/ams/meetings-events/ams-meetings/automated-vehicles-meteorology-summit1/ [Accessed 11th May 2023].

Anderson, A.R.S., Chapman, M., Drobot, S.D., Tadesse, A., Lambi, B., Wiener, G. et al. (2012) Quality of Mobile air temperature and atmospheric pressure observations from the 2010 development test environment experiment. *Journal of Applied Meteorology and Climatology*, 51, 691–701. Available from: https://doi.org/10.1175/JAMC-D-11-0126.1

AZDOT. (2021) Dust detection system ready for action this monsoon season. Available from: https://azdot.gov/blog-article/dust-detection-system-ready-action-monsoon-season [Accessed 20th April 2023].

Bartos, M., Park, H., Zhou, T., Kerkez, B. & Vasudevan, R. (2019) Windshield wipers on connected vehicles produce high-accuracy rainfall maps. *Scientific Reports*, 9, 170. Available from: https://doi.org/10.1038/s41598-018-36282-7

Bell, Z., Cornford, D. & Bastin, L. (2015) How good are citizen weather stations? Addressing a biased opinion. *Weather*, 70(30), 75–84. Available from: https://doi.org/10.1002/wea.2316

Bell, Z., Dance, S.L. & Waller, J.A. (2022) Exploring the characteristics of a vehicle-based temperature dataset for kilometre-scale data assimilation. *Meteorological Applications*, 29, e2058. Available from: https://doi.org/10.1002/met.2058

Benko, M. (2012) Road weather forecasts and MDSS in Slovakia. Proceedings of SIRWEC 2012, SIRWEC, Helsinki, Finland. Available from: https://sirwec.org/wp-content/uploads/2022/04/Helsinki-30.pdf

Bogaerts, T., Watelet, S., De Bruyne, N., Thoen, C., Coopman, T., Van Den Bergh, J. et al. (2022) Leveraging artificial intelligence and Fleet sensor data towards a higher resolution road weather model. *Sensors*, 22(7), 2732.

Chapman, M., Drobot, S., Anderson, A., Burghardt, C., 2013. Results from the Integrated Mobile Observations Study. (No. FHWA-JPO-13-066), 157.

Chapman, M., Drobot, S., Jensen, T. & Johansen, C. (2010) Using vehicle probe data to diagnose road weather conditions – results from the Detroit Intellidrive(SM) field study. *Transportation Research Record*, 2169, 116–127. Available from: https://doi.org/10.3141/2169-13

Coudert, O. (2017) Short term alarm system for road weather. Proceedings of the XVth International Winter Road Congress, PIARC, Gdańsk, Poland, T3-4. Available from: https://proceedings-gdansk2018.piarc.org/en/documents/session-documents/2270.htm

Crevier, L.-P. & Delage, Y. (2001) METRo: a new model for road-condition forecasting in Canada. *Journal of Applied Meteorology and Climatology*, 40, 2026–2037. Available from: https://doi.org/10.1175/1520-0450(2001)040<2026:MANMFR>2.0.CO;2

Dong, Y., Zhong, Y., Yu, W., Zhu, M., Lu, P., Fang, Y. et al. (2019) Mcity Data Collection for Automated Vehicle Study. arXiv: 1912.06258. Available from: https://arxiv.org/abs/1912.06258

Drobot, S., Anderson, A.R.S., Burghardt, C. & Pisano, P. (2014) U.S. public preferences for weather and road condition information. *Bulletin of the American Meteorological Society*, 95, 849–859. Available from: https://doi.org/10.1175/BAMS-D-12-00112.1

Drobot, S., Chapman, M., Pisano, P.A. & McKeever, B.B. (2010) *Using vehicles as Mobile weather platforms, data and mobility, advances in intelligent and soft computing*. Berlin, Heidelberg: Springer, pp. 203–213. Available from: https://doi.org/10.1007/978-3-642-15503-1_18

FCC. (2020) FCC Modernizes 5.9 GHz Band to Improve Wi-Fi and Automotive Safety. Available from: https://www.fcc.gov/document/fcc-modernizes-59-ghz-band-improve-wi-fi-and-automotive-safety-0 [Accessed 29th April 2023].

FCC. (2023) Request for Waiver of 5.9 GHz Band Rules to Permit Initial Deployment of Cellular Vehicle-to-Everything Technology. https://docs.fcc.gov/public/attachments/DA-23-343A1.pdf (Accessed 4.29.23).

FHWA. (2023) Weather data environment. Available from: https://wxde.fhwa.dot.gov/ [Accessed 30th April 2023].

Goberville, N., El-Yabroudi, M., Omwanas, M., Rojas, J., Meyer, R., Asher, Z. et al. (2020) Analysis of lidar and camera data in real-world weather conditions for autonomous vehicle operations. *SAE International Journal of Advances and Current Practices in Mobility*, 2(5), 2428–2434. Available from: https://doi.org/10.4271/2020-01-0093

Goberville, N.A., Prins, K.R., Kadav, P., Walker, C.L., Siems-Anderson, A.R. & Asher, Z.D. (2023) Snow coverage estimation using camera data for automated driving applications. *Transportation Research Interdisciplinary Perspectives*, 18, 100766. Available from: https://doi.org/10.1016/j.trip.2023.100766

Hintz, K.S., Vedel, H. & Kaas, E. (2019) Collecting and processing of barometric data from smartphones for potential use in numerical prediction data assimilation. *Meteorological Applications*, 26(4), 733–746. Available from: https://doi.org/10.1002/met.1805

ITS JPO. (2020) Connected vehicle. Available from: https://www.its.dot.gov/research_areas/WhitePaper_connected_vehicle.htm [Accessed 30th April 2023].

ITS JPO. (2021) Wyoming (WY) DOT Pilot. Available from: https://www.its.dot.gov/pilots/pilots_wydot.htm [Accessed 30th April 2023].

Juga, I., Nurmi, P. & Hippi, M. (2013) Statistical modelling of wintertime road surface friction. *Meteorological Applications*, 20, 318–329. Available from: https://doi.org/10.1002/met.1285

Karsisto, V. & Lovén, L. (2019) Verification of road surface temperature forecasts assimilating data from Mobile sensors. *Weather and Forecasting*, 34, 539–558. Available from: https://doi.org/10.1175/WAF-D-18-0167.1

Knight, S., Smith, C. & Roberts, M. (2010) Mapping Manchester's urban Heat Island. *Weather*, 65(7), 188–193.

Kutila, M., Pyykonen, P., Holzhuter, H., Colomb, M., Duthon, P., 2018. Automotive lidar performance verification in fog and rain. 21st international conference on intelligent transportation systems (ITSC). 1695–1701.

Lee, M.-S. & Nelson, D. (2018, 130) Utilization of AVL/GPS Technology: Case Studies. (No. CR 16-01). Available from: http://clearroads.org/wp-content/uploads/dlm_uploads/FR_CR.16-01_Final.pdf

Lopes, P.C., da Silva, J.C.S., Guarieiro, L.L.N. & Moreira, D.M. (2021) Study of environmental data from vehicle's sensors and its aplicability to complement climate mapping from automatic meteorological stations and assess covid-19 impact. *AI Perspectives & Advances*, 3, 5. Available from: https://doi.org/10.1186/s42467-021-00013-y

Lusikka, T., Leviäkangas, P. & Konttaniemi, H. (2019) Winter Road Management Business Ecosystem for Industrial Internet Applications. Preproceedings of the XXVIth International World Road Congress, PIARC, Abu Dhabi, UAE. Available from: https://pre-proceedings-abudhabi2019.piarc.org/ressources/files/2/IP0116-Lusikka-E-Full.pdf

Madaus, L.E. & Mass, C.F. (2017) Evaluating smartphone pressure observations for mesoscale analyses and forecasts. *Weather and Forecasting*, 32, 511–531. Available from: https://doi.org/10.1175/WAF-D-16-0135.1

Mahoney, W.P. & O'Sullivan, J.M. (2013) Realizing the potential of vehicle-based observations. *Bulletin of the American Meteorological Society*, 94, 1007–1018. Available from: https://doi.org/10.1175/BAMS-D-12-00044.1

Manfredi, J., Walters, T., Wilke, G., Osborne, L., Hart, R., Incrocci, T., Schmidt, T., 2005. Road Weather Information System Environmental Sensor Station siting guidelines. (No. FHWA-HOP-05-026), 46.

Marquès, E., Masson, V., Naveau, P., Mestre, O., Dubreuil, V. & Richard, Y. (2022) Urban Heat Island estimation from crowdsensing thermometers embedded in personal cars. *Bulletin of the American Meteorological Society*, 103, E1098–E1113. Available from: https://doi.org/10.1175/BAMS-D-21-0174.1

Mercelis, S., Watelet, S., Casteels, W., Bogaerts, T., Van den Bergh, J., Reyniers, M. et al. (2020) Toward detection of road weather conditions using large-scale vehicle fleets. 91st IEEE conference on vehicle technology, IEEE, Antwerp, Belgium. Available from: https://ieeexplore.ieee.org/document/9128484

Mitretek Systems. (1999) Surface transportation weather decision support requirements – executive summary, version 1.0. Available from: https://rosap.ntl.bts.gov/view/dot/2203

Muller, C.L., Chapman, L., Johnston, S., Kidd, C., Illingworth, S., Foody, G. et al. (2015) Crowdsourcing for climate and atmospheric sciences: current status and future potential. *International Journal of Climatology*, 35, 3185–3203. Available from: https://doi.org/10.1002/joc.4210

O'Hara, T., McClean, F., Villalobos Herrera, R., Lewis, E. & Fowler, H.J. (2023) Filling observational gaps with crowdsourced citizen science rainfall data from the met Office weather observation website. *Hydrology Research*, 54, 547–556. Available from: https://doi.org/10.2166/nh.2023.136

Pisano, P., Stern, A. & Mahoney, W. (2005) The US Federal Highway Administration Winter Road Maintenance Decision Support System (MDSS) Project: Overview and Results.

Pisano, P.A., Huft, D.L. & Stern, A.D. (2006) Deployment of maintenance decision support systems for winter operations, transportation research circular E-C098. Available from: https://trid.trb.org/view/786928

Rasmussen, E.N., Straka, J.M., Davies-Jones, R., Doswell, C.A., Carr, F.H., Eilts, M.D. et al. (1994) Verification of the origins of rotation in tornadoes experiment: VORTEX. *Bulletin of the American Meteorological Society*, 75, 995–1006. Available from: https://doi.org/10.1175/1520-0477(1994)075<0995:VOTOOR>2.0.CO;2

Rothenberg, D. (2023) Driving hyper-local weather information with autonomous vehicles. 39th conference on environmental information processing technologies, American Meteorolgical Society, Denver, CO, 4B.1. Available from: https://ams.confex.com/ams/103ANNUAL/meetingapp.cgi/Paper/412555

Sass, B.H. (1992) A numerical model for prediction of road temperature and ice. *Journal of Applied Meteorology and Climatology*, 31, 1499–1506. Available from: https://doi.org/10.1175/1520-0450(1992)031<1499:ANMFPO>2.0.CO;2

Sass, B.H. (1997) A numerical forecasting system for the prediction of slippery roads. *Journal of Applied Meteorology and Climatology*, 36, 801–817. Available from: https://doi.org/10.1175/1520-0450(1997)036<0801:ANFSFT>2.0.CO;2

Schneider, W., Crow, M., Holik, W.A., Bakula, C., Maistros, A.R., Gould, Z.T. et al. (2017) University of Akron, 2017. Evaluation of the GPS/AVL systems for snow and ice operations resource management. (No. FHWA/OH-2017-31). Available from: https://rosap.ntl.bts.gov/view/dot/32513

Siems-Anderson, A., Lee, J.A., Brown, B., Wiener, G. & Linden, S. (2020) Impacts of assimilating observations from connected vehicles into a numerical weather prediction model. *Transportation Research Interdisciplinary Perspectives*, 8, 100253. Available from: https://doi.org/10.1016/j.trip.2020.100253

Siems-Anderson, A., Walker, C., Kadav, P. & Asher, Z. (2023) Automated, Electric Vehicle Operations During Adverse Weather Conditions. Proc. of the XXVII World Road Congress, PIARC, Prague, Czech Republic. Available from: https://pre-proceedings-prague2023.piarc.org/ressources/files/source/3/IP0315-Siems-Anderson-E-Amended.pdf

Siems-Anderson, A.R., Walker, C.L., Wiener, G., Mahoney, W.P. & Haupt, S.E. (2019) An adaptive big data weather system for surface transportation. *Transportation Research Interdisciplinary Perspectives*, 3, 100071. Available from: https://doi.org/10.1016/j.trip.2019.100071

Siems-Anderson, A., Wiener, G., Brummet, T., Linden, S., Petzke, W., McCarthy, P. et al. (2017) Use of the Pikalert(R) system in the Wyoming Department of Transportation Connected Vehicle Pilot Deployment. *Routes/Roads*, 375, 27–30.

Skamarock, W.C., Klemp, J.B., Dudhia, J., Gill, D.O., Barker, D.M., Duda, M.G. et al. (2008) A Description of the Advanced Research WRF Version 3. (No. NCAR/TN-475+STR). https://doi.org/10.5065/D68S4MVH

Thota, J., Abdullah, N.F., Doufexi, A. & Armour, S. (2020) V2V for vehicular safety applications. *IEEE Transactions on Intelligent Transportation Systems*, 21, 2571–2585. Available from: https://doi.org/10.1109/TITS.2019.2920738

Vaisala. (2010) Vaisala Maintenance Decision Support System (MDSS) Guidance for 21st Century Roadway Operations. Available from: https://www.vaisala.com/sites/default/files/documents/MDSS-Datasheet-B210938EN-A-LOW-v6.pdf

Walker, C.L., Boyce, B., Albrecht, C.P. & Siems-Anderson, A. (2020) Will weather dampen self-driving vehicles? *Bulletin of the American Meteorological Society*, 101, E1914–E1923. Available from: https://doi.org/10.1175/BAMS-D-19-0035.1

Walker, C.L., Siems-Anderson, A.R., Towler, E., Dugger, A., Gaydos, A., Wiener, G. et al. (2022) Development of a roadway flood severity index. 38th conference on environmental information processing technologies, American Meteorological Society, Houston, TX, 3B.3. Available from: https://ams.confex.com/ams/102ANNUAL/meetingapp.cgi/Paper/394900

Zachrisson, B. & Hägg, J. (2023) Floating Car Data as an Enabler for More Efficient Winter Maintenance Operations. Proc. of the XXVII World Road Congress, PIARC, Prague, Czech Republic. Available from: https://pre-proceedings-prague2023.piarc.org/ressources/files/source/2/IP0638-Zachrisson-E.pdf

Zachrisson, B., Hägg, J., Frank, H., Petersson, J. & Noren, O. (2023) Probe Vehicle Data as Input Source for Road Maintenance. Proc. of the XXVII World Road Congress, PIARC, Prague, Czech Republic. Available from: https://proceedings-prague2023.piarc.org/ressources/files/source/5/IP0641-Zachrisson-E.doc.pdf

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