Vehicles as sensors: high-accuracy rainfall maps from windshield wiper measurements

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ABSTRACT

Connected vehicles are poised to transform the field of environmental sensing by enabling acquisition of scientific data at unprecedented scales. Drawing on a real-world dataset collected from almost 70 connected vehicles, this study generates improved rainfall estimates by combining weather radar with windshield wiper observations. Existing methods for measuring precipitation are subject to spatial and temporal uncertainties that compromise high-precision applications like flash flood forecasting. Windshield wiper measurements from connected vehicles correct these uncertainties by providing precise information about the timing and location of rainfall. Using co-located vehicle dashboard camera footage, we find that wiper measurements are a stronger predictor of binary rainfall state than traditional stationary gages or radar-based measurements. We introduce a Bayesian filtering framework that generates improved rainfall estimates by updating radar rainfall fields with windshield wiper observations. We find that the resulting rainfall field estimate captures rainfall events that would otherwise be missed by conventional measurements. We discuss how these enhanced rainfall maps can be used to improve flood warnings and facilitate real-time operation of stormwater infrastructure.

Introduction

Accurate rainfall measurements are essential for the effective management of water resources\textsuperscript{1}. Historical rainfall records are used extensively in the design of water infrastructure\textsuperscript{2}, while at finer scales, real-time rainfall measurements are an integral component of flood forecasting systems\textsuperscript{3}. Despite the central role that precipitation measurements play in the design and operation of water infrastructure, current methods for measuring precipitation often do not provide the spatial resolution or measurement certainty required for real-time applications\textsuperscript{3}. As the demand for real-time precipitation data increases, new sensing modalities are needed to address deficiencies found in conventional data sources.

The need for high-resolution precipitation estimates is perhaps best illustrated by the problem of urban flash flooding. Flooding is the number one cause of natural disaster fatalities worldwide, with flash floods accounting for a majority of flooding deaths in developed countries\textsuperscript{4}. Despite the risks posed by flash flooding, there is “no existing model [that is] capable of making reliable flash flood forecasts in urban watersheds”\textsuperscript{5}. Flash flood forecasting is to a large extent hindered by a lack of high-resolution precipitation data, with spatial resolutions of < 500 m and temporal resolutions of 1-15 minutes required for urban areas\textsuperscript{5,6}.

Contemporary rain measurement technologies—such as stationary rain gages and weather radar—struggle to achieve the level of precision necessary for flash flood forecasting. While rain gages have long served as a trusted source of surface-level precipitation measurements\textsuperscript{7}, they often fail to capture the spatial variability of rain events, especially during convective storms\textsuperscript{8–10}. This inability to resolve spatial patterns in rainfall is made worse by the fact that the number of rain gages worldwide is rapidly declining\textsuperscript{1}. Weather radar is a useful tool for capturing the spatial distribution of rainfall. However, radar-rainfall estimates are subject to large spatial and temporal uncertainties\textsuperscript{11–14}. Additionally, weather radar tends to show systematically large biases for major flood events, and may perform poorly for small watersheds\textsuperscript{6}, making urban flood forecasting problematic.

The rise of connected and autonomous vehicles offers an unprecedented opportunity to enhance the density of environmental measurements\textsuperscript{15,16}. While dedicated sensor networks are expensive to deploy and maintain, fleets of connected vehicles can capture real-time data at fine spatial and temporal scales through the use of incidental onboard sensors. With regard to rainfall measurement, windshield wiper activity offers a novel means to detect the location and timing of rainfall with enhanced precision. When used in conjunction with modern signal processing techniques, wiper-based sensing offers several attractive properties: (i) vehicles achieve vastly improved coverage of urban areas, where flood monitoring is important; (ii) windshield...
Figure 1. Overview of the study area on June 12, 2014. Blue circles represent rain gages. Vehicle paths are shown as green lines, while roads are shown in gray. A radar overlay shows the average precipitation intensity as estimated by radar.

Wiper intensity is easy to measure and requires little overhead for processing (as opposed to video or audio data); and (iii) vehicle-based sensing can be readily scaled as vehicle-to-infrastructure communication becomes more widespread. Moreover, many new vehicles come equipped with optical rain sensors that enable direct measurement of rainfall intensities. When paired with data assimilation techniques, these sensors may enable even higher-accuracy estimation of rainfall fields compared to wipers alone.

While a small number of studies have investigated vehicle-based precipitation measurements, the results of these studies are strictly based on simulated wiper data instead of real measurements. As such, the premise that windshield wiper data can be used to improve rainfall estimates has never been verified using a large real-world dataset. Hill (2015) combines simulated binary (wet/dry) rainfall sensors with weather radar observations to generate improved areal rainfall estimates, which are then validated against rainfall fields produced by interpolation of tipping-bucket rain gages. Similarly, Haberlandt (2010) combines simulated vehicle wiper measurements with rain gage observations to improve rainfall field estimates, and then validates the resulting product against weather radar. Although these studies highlight the potential for vehicle-based measurements to improve the spatial and temporal resolution of rainfall estimates, their findings have not yet been validated using data from real-world connected vehicles.

To address these challenges, this study leverages windshield wiper measurements collected from nearly 70 vehicles to produce corrected rainfall maps (see Figure 1 for a description of the study area and data sources). In the first part of this paper, we demonstrate that windshield wiper measurements offer a reliable indicator of rainfall by comparing wiper measurements against dashboard camera footage that indicates the ground truth binary rainfall state (raining/not raining). In the second part of this paper, we develop a Bayesian data fusion procedure that combines weather radar with vehicle-based wiper measurements to produce an updated probabilistic rainfall field map. We validate this novel data product by showing that it is more effective than the original radar data at predicting the binary rainfall state. Finally, we discuss how these enhanced rainfall maps can be used to improve flood warnings and facilitate real-time operation of stormwater infrastructure.
Results

Figure 2. Analysis of a single vehicle trip occurring from 21:46 - 22:26 on August 11, 2014. The top two panels show video footage during the rainy (left) and dry (right) segments of the trip. The bottom left panel shows a map of the vehicle’s trip, with the wiper intensity indicated by color. A radar overlay shows the average rainfall intensity over the 40-minute time period. Blue circles represent the gages nearest to the vehicle path. The two bottom right panels show the precipitation intensity as estimated by radar and gage measurements (center), and the 1-minute average wiper intensity (bottom).

Windshield wipers improve binary rainfall detection

Windshield wiper measurements enhance rainfall estimation by enabling greater certainty about the timing and location of rainfall. While wiper intensity is generally a poor predictor of rainfall intensity (see Figure S1 in the Supplementary Information), we find that wiper status (on/off) is a stronger predictor of binary rainfall state than either radar or gage-based measurements. This result suggests that vehicle-based measurements can be used to validate and correct rainfall fields derived from conventional data sources.

Wiper measurements provide a more accurate indicator of binary rainfall state than either radar or gage measurements. We determine the binary classification performance for each technology (gages, radar and wipers) by comparing the measured rainfall state with co-located dashboard video footage. Dashboard video is taken to represent the ground truth, given that the presence or absence of rainfall can readily be determined by visually inspecting the windshield for raindrops. Figure 2 shows an example of co-located radar, gage, wiper and camera measurements for a single vehicle trip. In this case, rainfall is visible during the first half of the trip (top left). Aggregating these cross-comparisons for every vehicle trip across three storm events, we find that wiper status is the best estimator of binary rainfall state, with a true positive rate (TPR) of 93.1%, and a true negative rate (TNR) of 98.2%. By comparison, weather radar achieves a smaller TPR of 89.5%, while stationary gages show a much smaller TPR of 44.5% (see Table 2). These results can partly be explained by the superior spatial and temporal resolution of the vehicle-based measurements. Wipers detect intermittent changes in rainfall at a temporal resolution on the order of seconds, while radar and gage measurements can only detect the average rate over a 5-minute period. When ground truth camera observations are collected at a 3-second temporal resolution, the benefit of wiper measurements over radar measurements becomes even more pronounced, with a TPR advantage of 5.2%, a TNR advantage of 7.7%, and an overall wiper TPR of 97.0% (see the supplementary note on factors affecting binary detection performance). The results of this analysis suggest that conventional rainfall measurement technologies can be enhanced through the inclusion of vehicle-based measurements.
### Table 1. Classification performance of each rainfall measurement technology

| Metric                  | Gage | Radar | Wiper |
|-------------------------|------|-------|-------|
| True Positive Rate (%)  | 44.5 | 89.5  | 93.1  |
| True Negative Rate (%)  | 96.7 | 97.5  | 98.2  |

The true positive rate indicates the percentage of instances where the given technology successfully detects rainfall when rainfall is actually occurring. The true negative rate indicates the percentage of instances where the technology does not detect rainfall when rainfall is not occurring.

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#### Assimilation of wiper data yields corrected rainfall maps

Based on the observation that wiper measurements are a strong binary predictor of rainfall, we develop a Bayesian filtering framework that combines radar rainfall estimates with wiper observations to generate corrected rainfall maps. Radar is used to estimate a prior distribution of rainfall intensities. This prior is then updated with wiper observations to produce a corrected rainfall field. The results of this filtering procedure are demonstrated in Figure 3, which shows the original rainfall field (top) along with the corrected rainfall field (bottom). In some cases (left panel), vehicles detect no rain in regions where radar had previously estimated rain. In these cases, the updated product reduces the rainfall field in the proximity of the vehicle. In other cases (right panel), the updated product predicts rainfall in regions where little to no rainfall was observed in the original dataset. This outcome shows that windshield wiper activity is sensitive to intermittent rainfall events that radar may not otherwise detect.

To see the full evolution of the rainfall field under both the original and corrected data sets, refer to Video S1.

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**Figure 3. Original and updated rainfall maps.** Top (left and right): Original weather radar rainfall intensity map. Radial radar scans have been resampled to a 1 km grid to ensure computational tractability. Bottom (left and right): updated rainfall intensity map, combining radar data with wiper measurements using the Bayesian filter. In the bottom left panel, a “hole” in the rainfall field occurs when a vehicle detects no rain in a location where radar alone estimated rain. In the bottom right panel, vehicles detect rainfall where radar previously did not detect rainfall.

The wiper-corrected rainfall field predicts the binary rainfall state with greater accuracy than the radar-only data product. To validate the wiper-corrected rainfall field, we use an iterated “leave-one-out” approach, in which an updated rainfall field is generated while excluding a vehicle, and the resulting data product is compared against the measured rainfall state of the omitted vehicle. Repeating this process for each vehicle yields the receiver operator characteristics shown in Figure 4. These
curves map the relationship between the TPR and TNR for both the original rainfall field (radar only) and the corrected rainfall field (radar and wiper). Curves located closer to the upper-left corner (i.e. those with a larger area under the curve) exhibit the best performance, given that they have a large true positive rate and a small false negative rate. Based on these curves, it can be seen that the corrected data product performs consistently better than the original radar product at predicting the presence or absence of rain, with a TPR and TNR close to unity. These results confirm that inclusion of vehicle-based measurements enables improved prediction of the underlying rainfall field.

**Discussion**

The enhanced rainfall maps developed in this study have the potential to assist in the real-time operation of transportation and water infrastructure. In particular, high accuracy rainfall field estimates will enable improved prediction of flash floods in urban centers, and will help to inform real-time control strategies for stormwater systems. As mentioned previously, flash flood forecasting is contingent on high-resolution areal rainfall estimates, with accurate measurements on the order of 500 m or finer required for forecasting in urban areas. By enabling real-time validation and filtering of radar rainfall estimates, vehicle-based sensors may help fill measurement gaps and improve the prediction of flood events near roadways. Monitoring of roadways is especially important given that in the US, roughly 74% of flood fatalities are vehicle related. While the vehicles used in this study provide only binary measurements of rainfall state, many newer vehicles feature optical rain sensors that are capable of measuring precipitation rate directly. When combined with the Bayesian sensor fusion framework described in this study, these optical rain sensors may enable robust mapping of rainfall volumes at the fine spatial and temporal scales needed for high-accuracy flash flood forecasting. Moreover, as connected and autonomous vehicles become more widely adopted, the spatial coverage and measurement certainty of this new rainfall sensing modality will be even further enhanced.

In addition to assisting with flash flood response, high-precision rainfall data products may one day inform the operation of new “smart” water infrastructure. Recent work has highlighted the potential of “smart” water systems to mitigate water hazards through real-time control of distributed gates, valves and pumps. When informed by accurate and timely data, these systems can significantly reduce operating costs, prevent combined sewer overflows, and halt the degradation of aquatic ecosystems by adaptively reconfiguring water infrastructure in real time. However, recent findings suggest that optimal control strategies for “smart” water systems are highly sensitive to the location, timing and intensity of rainfall inputs. In this regard, the wiper-corrected rainfall product presented in this study may help to enable more fine-grained control of water infrastructure by reducing uncertainty in conventional rainfall field estimates.

![Figure 4. Binary classification performance of the updated rainfall product.](image)

Receiver operator characteristic (ROC) curves indicate the rainfall state prediction accuracy for the original radar estimate and the updated (wiper-corrected) data product. The area under the curve (AUC) measures overall classification performance.
Conclusions

This study generates enhanced probabilistic rainfall maps by combining conventional radar-based precipitation fields with ubiquitous windshield wiper measurements from almost 70 unique vehicles. We find that while windshield wiper intensity is a poor predictor of rainfall intensity, wiper activity is a stronger predictor of binary rainfall state than conventional radar and gage-based data sources. With this result in mind, we develop a novel Bayesian filtering framework that combines a radar-based rainfall prior with binary windshield wiper observations to produce an updated rainfall map. We find that the Bayesian filtering process is effective at detecting changes in the rainfall field that conventional measurement technologies may otherwise miss. We validate the updated rainfall data product by assessing its ability to reproduce the binary rainfall state anticipated by an omitted vehicle. Based on this analysis, we find that the corrected rainfall field is better at predicting the binary rainfall state than the original radar product. As connected vehicles become more widespread, the ubiquitous sensing approach proposed by this study may one day help to inform real-time warning and control systems for water infrastructure by providing fine-grained estimates of the rainfall field.

Materials and Methods

Evaluating vehicle-based measurements

In the first part of this study, we assess the degree to which windshield wiper activity serves as a proxy for both rainfall intensity and binary rainfall state. First, wiper measurements are compared against conventional rainfall measurement technologies to determine if there is a direct relationship between wiper intensity and rain intensity. Next, we assess the degree to which each data source reflects the ground truth rainfall state by comparing measurements from all three sources (gages, radar and wipers) with vehicle-based video footage. Video footage provides instantaneous visual confirmation of the rainfall state (raining or not raining), and is thus taken to represent the ground truth. We characterize the binary classification performance of each technology in terms of its true positive and true negative rates.

To ensure that our analysis is computationally tractable, we isolate the study to a subset of three storms in 2014. We assess the validity of our procedure for storms of different magnitudes by selecting a large storm (2014-08-11), a medium-sized storm (2014-06-28) and a small storm (2014-06-12). Storms are selected during the summertime months to avoid conflating rainfall measurements with snow measurements. The year 2014 is chosen because it is the year for which the greatest number of vehicles are available. Unless otherwise specified, data are co-located using a nearest neighbor search. For comparison of wiper and gage readings, we select only those gages within a 2 km range of any given vehicle.

Data sources

We consider four data sources: (i) stationary rain gages, (ii) weather surveillance radar, (iii) vehicle windshield wiper data, and (iv) vehicle dashboard camera footage. We provide a brief description of each data source here:

Gage data are obtained from personal weather stations maintained by the Weather Underground. Within the city of Ann Arbor (Michigan), Weather Underground hosts 21 personal weather stations, each of which yield rainfall estimates at a time interval of approximately 5 minutes. Locations of gages are indicated by blue circles in Figure 1. Although verified gage data from the National Weather Service (NWS) and the National Oceanic and Atmospheric Administration (NOAA) are available, Weather Underground gages are selected because (i) NOAA and NWS each maintain only a single gage in the city of Ann Arbor, meaning that intra-urban spatial variations in precipitation intensity cannot be captured, and (ii) the temporal resolution of NOAA and NWS gages are relatively coarse for real-time applications (with NOAA offering a maximum temporal resolution of 15 minutes and NWS offering a maximum temporal resolution of 1 hour).

Weather radar observations are obtained from NOAA’s NEXRAD Level 3 Radar product archive. We use the “Instantaneous Precipitation Rate” data product (p176). Radar precipitation estimates are obtained at a temporal resolution of 5 minutes, and a spatial resolution of 0.25 km by 0.5 degree (azimuth). Radar station KDTX in Detroit is used because it is the closest radar station to the City of Ann Arbor. Radial radar scans are interpolated to cartesian coordinates using a nearest neighbor approach.

Vehicle-based wiper intensities are obtained from the University of Michigan Transportation Research Institute (UMTRI) Safety Pilot Model Deployment database. For each vehicle, this dataset includes time series of latitude, longitude, and windshield wiper intensity at a temporal resolution of 2 milliseconds. Windshield wiper intensity is given on an ordinal scale from 0 to 3, with 0 indicating that the wiper is turned off, 1 representing the lowest wiper intensity, and 3 representing the highest wiper intensity. A wiper reading of 4 indicates that the vehicle’s “mister” is activated, distinguishing between wiper use for rain removal and wiper use for windshield cleaning. For the year 2014, 69 unique vehicles are available in the UMTRI dataset. However, typically less than ten vehicles are active at any given time during
the observation period. Vehicles with no sensor output or invalid readings were removed from the dataset prior to the analysis (see the Supplementary Note for more details).

**Camera observations** are also obtained from the UMTRI vehicle database\textsuperscript{25}. Located on the inside of each vehicle, cameras provide streaming video footage of the windshield, side-facing windows, rear-facing windows, and the driver. For the purposes of validation, we use the front-facing windshield camera. Camera frames are manually inspected for rain drops striking the windshield. Time intervals where rain is observed are classified as “raining”; similarly time intervals where no new droplets are observed are classified as “not raining”. Manual inspection and labeling of the video data was performed independently by two reviewers to ensure robustness.

**A Bayesian filtering framework**

In the second part of this study, we develop a Bayesian filtering framework that combines binary wiper observations with radar-based rainfall intensity measurements to generate corrected rainfall maps. In simple terms, the Bayesian filter generates an updated rainfall field map, in which binary (on/off) wiper measurements adaptively correct the underlying radar rainfall field. Windshield wiper status is taken to represent a measurement of the ground truth binary rainfall state, given that it is a better predictor of the binary rainfall state than radar- or gage-based measurements. Under this framework, four distinct cases are possible. If both the wiper and radar measure precipitation, the radar reading is taken to be correct, and the original rainfall state is represented as a random tuple $zzz = (q, I)$. Where $q$ is the location state (e.g. the latitude and longitude at the target), and $I$ is an information state (e.g. the precipitation intensity at the target) with all the random quantities indicated by bold italics. We denote by $M_t$ the event that sensors correctly measure the intensity, and by $M_t$ the event that sensors fail to measure the intensity correctly. The joint measurement likelihood at any time $t$ is given by:

$$ p(M_t|z, x_t) $$

where $x_t$ represents the locations of the sensors at time $t$. Equation 1 yields the probability distribution of precipitation intensity measurement at $q$ by sensors at $x_t$. The expected value of Equation 1 with respect to $I$ is equivalent to the rainfall intensity experienced at the location $q$. Because the effective range of the wipers is limited, we account for the probability of detection as a function of the distance between the sensor and the target. We denote by $D_t$ the event that sensors detect the target, and by $\overline{D}_t$ the event that sensors fail to detect the target at time $t$. The probability of detecting a target located at $q$ by sensors located at $x_t$, $p(D_t|q, x_t)$, is taken to decay with increasing distance to the sensor. Using the law of total probability, the conditional probability of a correct measurement is then given by:

$$ p(M_t|z, x_t) = p(M_t|z, D_t, x_t)p(D_t|q, x_t) + p(M_t|z, \overline{D}_t, x_t)p(\overline{D}_t|q, x_t) $$

(2)

where $D_t$ is conditionally independent of $I$ when conditioned on $q$. For example, consider $x_t = (0, 0)$, and $q = (q_1, q_2)$. If the decay function is taken to be a 2D Gaussian centered at $x_t$ with covariance matrix $\sigma I$ where $I$ is a 2 by 2 identity matrix, then:

$$ p(D_t|q, x_t) = \eta_t \frac{1}{2\pi\sigma^2} \exp \left(-\frac{q_1^2 + q_2^2}{2\sigma^2}\right) $$

(3)

Where $\eta_t$ is a normalization constraint. If the target is not detected (i.e., $\overline{D}_t$), then the measurement is assumed to be unreliable, and the likelihood, $p(M_t|z, \overline{D}_t, x_t)$, is modeled using a prior distribution. If there is no prior information available, the function is modeled using a uniform distribution. Now let $b_t(z)$ represent the posterior probability of the precipitation intensity given a target location $q$ at time $t$. Using Bayes’ Theorem, $b_t(z)$ can be formulated:

$$ b_t(z) = \eta_t p(M_t|z, x_t)b_{t-1}(z), \quad t = 1, 2, \ldots $$

(4)
Where \( \eta_t \) is a normalization constant and \( b_0 \) is uniform if no information is available at \( t = 0 \). This filtering equation forms the basis of the rainfall field updating algorithm. To reduce computational complexity, the filtering operation is implemented using a Sequential Importance Resampling (SIR) Particle Filter\(^{27}\).

The results of the Bayesian sensor fusion procedure are evaluated by determining the proportion of instances where the combined data product is able to predict the binary rainfall state. We characterize the true and false positive rates for the largest storm event (2014-08-11) using an iterated “leave-one-out” cross-validation approach. First, a single vehicle is removed from the set of vehicles. The Bayesian update procedure is then executed using all vehicles except the excluded vehicle, and an updated rainfall map is generated. Next, the rainfall states predicted by the corrected rainfall field (radar and wiper) and the original rainfall field (radar only) are compared against the rainfall states predicted by the omitted vehicle. The performance of each data product is evaluated based on its ability to reproduce the binary rainfall state observed by the omitted vehicle. Performing this process iteratively yields the true and false positive rates for both the original (radar only) and updated (radar and wiper) rainfall fields. This procedure is repeated for each vehicle in the set of vehicles to generate Receiver-Operator Characteristic (ROC) curves, which characterize the true and false positive rates across an ensemble of simulations.

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**Acknowledgements**

Funding for this project was provided by MCubed (grant 985), the Ford Motor Company–University of Michigan Alliance (grant N022977), and the University of Michigan. Vehicle metadata and camera footage are provided courtesy of the University of Michigan Transportation Research Institute.

**Author contributions statement**

M.B. wrote the paper, performed the analysis, and helped with the implementation of the filtering algorithm. H.P. developed, implemented, and validated the filtering algorithm. T.Z. analyzed the dashboard camera data and assisted with analysis of the windshield wiper data. B.K. and R.V. originated the concept of the study, guided the development of the methods, and assisted in writing the paper. Additional inspection and labeling of vehicle dashboard footage was performed by Aditya Prakash Singh. All authors reviewed the manuscript.

**Additional information**

**Data access links**

Upon publication, code and data for this study will be made available at: [github.com/kLabUM/vehicles-as-sensors](https://github.com/kLabUM/vehicles-as-sensors).

**Competing financial interests statement**

The authors declare no competing interests.
Supplementary Materials

Supplementary note on binary detection performance

Binary detection performance is sensitive to a number of factors, including the temporal resolution of the ground truth data and the configuration of wiper sensors. While these factors can affect the magnitude of binary classification performance, under all scenarios considered, wiper measurements are a better detector of the binary rainfall state than either radar or gage measurements.

Binary detection performance can be affected by the temporal resolution at which the ground truth data is collected. To ensure robustness, labeling of vehicle footage was performed independently by two reviewers. The first reviewer labeled the observed rainfall state for each vehicle over all three days of the study period (2014-06-12, 2014-06-28, 2014-08-11) at a temporal interval of 1 minute. A second reviewer labeled the observed rainfall and wiper state for the largest storm event (2014-08-11) at an enhanced time resolution of roughly 3 seconds. Due to the time-intensive nature of labeling video data at this temporal resolution, and due to the strong agreement between the two labeled datasets, this second round of labeling was not performed for the remaining two days (2014-06-12 and 2014-06-28). Despite the difference in time resolution, manual labeling of the video data showed strong agreement. Taking the high-resolution dataset to represent the ground truth rainfall state (and aggregating the high-resolution dataset to the temporal resolution of the low-resolution dataset), the true positive rate of the low temporal-resolution camera observations was 92.6%, while the true negative rate was 99.3%. Agreement in terms of positive detection was lower due to the difference in temporal resolution between the two sources. The low-resolution camera observation dataset classifies each minute-long interval as either “raining” or “not raining”. However, the high-resolution ground truth dataset contains many instances in which part of a given minute-long interval contains rain, and part does not. Thus, when the high-resolution dataset is aggregated to match the resolution of the low-resolution dataset, there are more intervals where some amount of rain is detected (yielding more instances of positive detection overall). A similar mismatch occurs if the low-resolution dataset is interpolated to match the time resolution of the high-resolution dataset. This time resolution mismatch also affects comparisons between the ground truth and other data sources (e.g. wiper, radar and gages). In general, the difference in classification performance between data sources decreases when the ground truth dataset is aggregated in time. Differences in classification performance become more pronounced when a high-resolution ground truth dataset is used.

Many vehicles exhibited data quality issues such as non-reporting wiper sensors, malfunctioning wiper sensors, or unobservable wiper modes. These data quality issues may impact the performance of the wiper as a classifier, but are largely attributable to the fact that the data is taken from a pilot study in which sensor configurations are not standardized. For some vehicles, wiper sensors were simply not configured to report wiper data. In these instances, the reported wiper value was zero for the entire observation period even though wiper movement was observed during manual inspection of the dashboard footage. Vehicles for which wiper sensors were not configured were removed from the analysis. Other vehicles exhibited malfunctioning or poorly configured sensors. For instance, in some cases the wiper intensity fluctuated between 0 and 1 at a frequency on the order of milliseconds—a behavior which is clearly not possible for a human driver. Video footage confirmed that the sensor was malfunctioning during these time periods. Malfunctioning vehicles were also removed from the analysis. Perhaps the most common data quality issue, however, is that several vehicles exhibited unobservable wiper modes. In this case, sensors were configured to report some wiper intensity states but not others. For example, the sensor may report the wiper intensity when the wiper switch is in a “continuous” mode, but may not report the wiper intensity when the wiper is placed in a manual “wipe” mode. These cases could only be detected by manual inspection of the camera footage. These data issues can largely be attributed to the fact that the sensor data is taken from a pilot study in which sensor configurations vary from vehicle to vehicle. As manufacturers standardize sensor configurations for connected vehicles, the relevance of these issues is likely to diminish.

The performance of the wiper as a classifier can be improved by (i) comparing wiper data against a ground truth dataset obtained at a high temporal resolution, and (ii) correcting errors in the wiper sensor readings. When manual observations of the wiper state are used to correct unobservable wiper modes, and the resulting corrected wiper data is compared to the 3-second resolution camera observations, the binary classification performance over weather radar is significantly enhanced: the true positive rate of the wiper data is 5.2% higher than radar, while the true negative rate is 7.7% higher. Table S1 shows the true and false positive rates for all technologies (during the 2014-08-11 storm event) when these two conditions are met.
Figure 5. Comparison of radar, gage and wiper intensities for three storm events on 6/12/2014, 6/28/2014, and 8/11/2014. The left panel shows the distribution of radar precipitation measurements associated with each wiper intensity. The right panel shows the distribution of gage precipitation measurements associated with each wiper intensity for vehicles located within 2 kilometers of the gage. Note that the range limitation reduces the number of data points available. No clear relationship is observed between wiper intensity and rainfall intensity.
Table S1

| Metric               | Gage | Radar | Wiper |
|----------------------|------|-------|-------|
| True Positive Rate (%) | 55.1 | 91.8  | 97.0  |
| True Negative Rate (%) | 96.9 | 87.4  | 95.1  |

Table 2. Classification performance of each rainfall measurement technology when using high-temporal resolution ground truth data, and correcting misreporting wiper states. These binary performance metrics hold when (i) ground truth observations at a resolution of 2.4 seconds are used, and (ii) manual corrections are made to the wiper state according to the wiper state in the observed camera footage (i.e. unobservable wiper modes are corrected).
Video S1
Original rainfall field (top) vs. updated data product (bottom) for a large storm event on 2014-08-11. Vehicle paths can be seen in the bottom frame, with windshield wiper intensities indicated by greyscale intensity from off (white) to high intensity (dark grey).