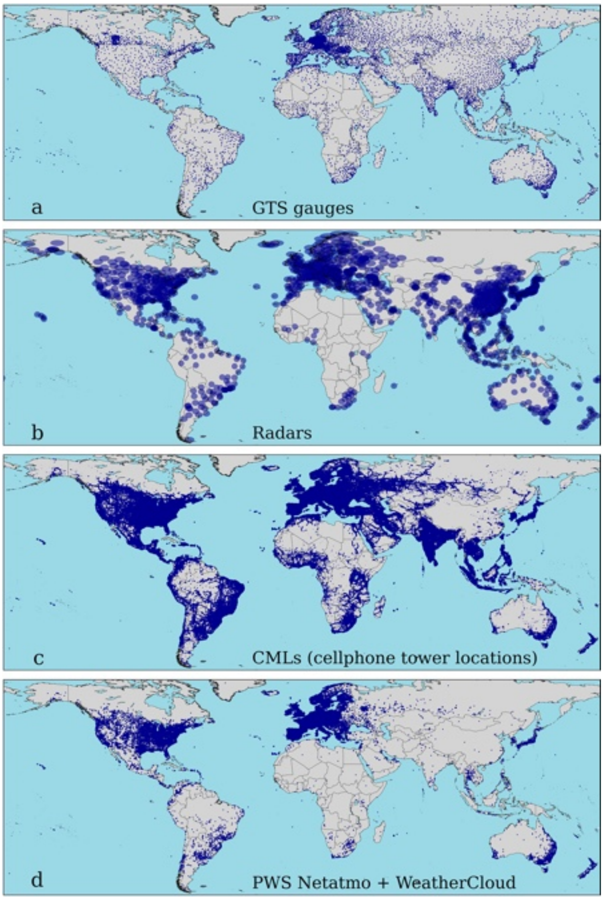

FIG. 1. Worldwide maps with estimated coverage for (a) GTS rain gauges, (b) ground-based weather radars, (c) CML (estimated cell phone tower locations obtained from the OpenCelliD project: https://opencellid.org/), and (d) PWS from the Netatmo (obtained through the Netatmo API: https://dev.netatmo.com/apidocumentation/weather) and WeatherCloud platforms. Methods and datasets are described in Overeem et al. (2024b), but for WeatherCloud gauge locations which have been downloaded from https://app.weathercloud.net/map on October 2024 and have been added to the PWS coverage map. Maps made with Natural Earth (free vector and raster map data © https://naturalearthdata.com).

and Technology (COST) Action Opportunistic Precipitation Sensing Network (OpenSense), running between 2021 and 2025 with currently (February 2025) 148 members from 35 countries, representing most major institutes and organizations in Europe working on this topic (https://opensenseaction.eu/). The main objective of OpenSense is to create a worldwide community of scientists, experts, and end users working with OS rainfall data.

The focus in OpenSense is on three types of sensors—commercial microwave links (CML), personal weather stations (PWS), and satellite microwave links (SML). A microwave link is a terrestrial telecommunication (backhaul) link between two cell phone towers that measures the (transmitted and) received signal levels. From the difference in power levels between wet and dry periods, the path-integrated attenuation can be computed. From this attenuation, the path-averaged rainfall intensity between a transmitting and a receiving antenna can be estimated. Uncertainties in CML rainfall retrieval are related primarily to separation of raindrop path-averaged attenuation from other sources of signal power losses, malfunctioning links, and sampling strategy. A personal weather station is a (generally) low-cost, nonprofessional rain gauge for personal use that can be connected online to upload and visualize the observations in near–real time. The number of PWS is constantly growing, generating very dense networks in many populated areas (Fig. 1d). Poor installation and/or maintenance may affect the precision of the observations. SML works according to similar principles as CML but with signals going between a GEO satellite and ground-based terminals. Potential error sources include difficulties representing tropospheric layers, adjustments of satellite operation, and gravitational perturbations. While SML has a clear potential, the number of application-oriented scientific papers is still very low, and furthermore, the technique is (currently) not on the same level as CML and PWS with respect to (pre)operational testing and evaluation at NMHS and similar organizations. We therefore focus this review primarily on CML and PWS, awaiting further development and applications of SML.

For further description of the three sensor types, as well as current practices and availability, see Fencl et al. (2024). Common to all the sensors is not only that they can provide rainfall observations with (very) high temporal resolution and (often) high spatial resolution (Table 1) but also that they are affected by various error sources that require careful quality control and filtering, as described above. Concerning the global distribution of CML (Fig. 1c), some areas with relatively poor coverage of conventional sensors stand out, e.g., parts of Asia, northeastern South America, and parts of Africa. The coverage of PWS (Fig. 1d) is generally highest in areas well covered also with GTS gauges, but the density is substantially higher, especially in North America and eastern South America.

The potential of OS rainfall data has been demonstrated and promoted in many proof-of-concept (case) studies, which have been summarized in a number of previous review or overview papers. Most of these papers focus solely on CML (e.g., Chwala and Kunstmann 2019; Messer 2018; Uijlenhoet et al. 2018; Lian et al. 2022; Zhang et al. 2023a) but some additionally include PWS (e.g., Muller et al. 2015). Wang et al. (2023a) provide a solid overview including both conventional and different opportunistic sensors. Studies on SML observations are surveyed in Giannetti and Reggiannini (2021). Most of these overview papers do include some information on applications but generally rather briefly and in a prospective sense. The only paper on OS rainfall data that has an explicit operational focus of which we are aware is Garcia-Marti et al. (2023), who describe how CML and PWS data could be integrated in NMHS' operations.

Despite their obvious potential, however, OS rainfall observations have not yet made much impact in terms of operational implementation and actual societal benefits, although efforts are ongoing at several NMHS (e.g., Hahn et al. 2022). This work intends to answer three main questions, representing past research, current state, and future prospects:

1) What is the scientific support for practical applications of OS rainfall data, e.g., in an operational setting?
2) How technically ready are different countries with respect to operational implementation of OS rainfall data?
3) What challenges remain and how can these be solved?

To answer the first question, we provide in section 3 a literature review with a specific focus on practical applications of OS rainfall data, demonstrating the potential added value. Examples include generation of merged spatiotemporal rainfall fields as well as subsequent use for nowcasting or hydrological prediction. The second question is answered in the form of a status report from the OpenSense community with focus on how close individual countries are to operational application of OS rainfall data in section 4. The report is based on a questionnaire with the purpose of acquiring an updated and complementary picture, as compared with published sources. Finally, remaining limitations and challenges that have prevented, and keep preventing, faster progress are described and discussed in section 5. These include quality assurance and uncertainty assessment in OS data as well as technical processing challenges related to, e.g., detection limits and network changes, geographical differences, e.g., with respect to availability of reference data and network density, and general limitations in access to OS data, e.g., related to pricing. Last, efforts needed to overcome the challenges and provide widespread societal benefit of OS rainfall data in a near future are outlined.

2. Methods

The results presented in this paper are based on two different activities. The first was the collection of references that investigate and utilize OS rainfall data from a perspective that relates to (operational) application and, in turn, societal benefit. We have divided these references into two main categories:

1) Rainfall mapping: This category contains investigations that present and demonstrate how OS rainfall data, individually or combined with conventional observations (e.g., weather radar), are used to generate spatiotemporal gridded rainfall maps. We consider this mapping, including quality control and assurance, a required first step toward operational applications. We distinguish between mapping based on one type of OS and on OS rainfall data merged with conventional observations, respectively.
2) Subsequent applications: Here, we include investigations where the quantitative rainfall products are used in subsequent prediction or simulation, in two subcategories. The first is rainfall nowcasting, i.e., short-term observation-based forecasting. The second subcategory is hydrological prediction, where OS-based rainfall inputs are used for hydrological simulation and discharge/flood forecasting. These subcategories emerged from the literature as the two main fields of OS rainfall application.

The collection of references was made primarily by a series of comprehensive searches in the Scopus (Scopus 2025), Web of Science (Clarivate Analytics 2025), and Dimensions (Dimensions 2025) platforms. All queries included names and abbreviations of the three opportunistic sensors considered in this paper and were limited to published peer-reviewed papers in English with only a few exceptions. We opted to impose the criterion on peer review since such publications are deemed to showcase credible applications of OS data as they have undergone rigorous evaluation. On the other hand, this criterion resulted in omitting some publications from the review, such as conference contributions or reports. The resulting lists of publications were thoroughly analyzed by the author team, supplemented by additional contributions identified through expert knowledge and targeted searches. Some challenges in identification and selection of relevant publications were encountered. First, the terminology used in this context is diversified as the field is still maturing, which hampered the literature search. For example, PWS observations can be referred to as “personal data,” “crowdsourced data,” “citizen data,” or just “citizen science,” and CML data can be called, e.g., “cellular communication interference” or just “telecommunication signals.” Second, the intention was to include only reasonably matured applications of OS rainfall data demonstrating real-world operational potential, in contrast to proof-of-concept studies at an earlier stage. Therefore, publications presenting, e.g., calibration of models describing the relationship between CML attenuation and rainfall rate, evaluation of OS data from comparisons to observations from conventional meteorological networks, and CML application to discriminate between wet or dry periods were excluded from the final selection of papers. The limit between the two groups of papers is not clear cut but there is a gray zone of studies where we have had to make subjective decisions. There is an inherent trade-off between the “breadth” (i.e., the number of publications included) and the “depth” (i.e., the exclusive selection of the most relevant papers), and we have made all efforts possible within the resources given to make a relevant and well-balanced selection.

The second activity was the distribution of a questionnaire within the OpenSense community, to survey the current status with respect to OS rainfall data access and application. The members of OpenSense include representatives of companies and various organizations (typically universities and NMHS) who responded on behalf of their own organization and, in some cases, other organizations present in the country. The questions focused on the types of OS rainfall observations that are currently used or planned, the sources of the data, and whether the data were in the research phase or being developed as an operational product. To quantify the latter aspect, we define an index named readiness for routine operation (RRO), which can be seen as a simplified and customized version of the widely used technology readiness level (TRL) concept. We divide RRO into the following categories:

1) countries that have conducted first experiments, experimented with small OS rainfall datasets;
2) countries with increased experience, e.g., through large-scale validation studies and/or experimental usage of OS rainfall data in applications; and
3) countries where the respective OS is used either operationally or in a quasi-operational state, either at a water authority or a university.

The categories 1, 2, and 3 roughly correspond to TRLs 1–3, 4–6, and 7–9 as defined in European (EU) Horizon (e.g., EU 2014). The survey also inquired about merged products that include the combination of conventional and opportunistic sensors, as well as the main applications of OS rainfall data. The questionnaire was originally sent out in 2022 and then updated in 2023 and 2024 to ensure that the current state is properly described.

It should be noted that the OpenSense COST action is open to all participants from around the world, and its members have widely publicized OpenSense to gather experts interested in OS rainfall data under this overarching action. Although there are representatives from the Global South countries in the action, the outreach of the questionnaire is biased toward the Global North. The literature review presented in this paper can reduce this bias, i.e., to provide a complementary global overview of the applications of OS rainfall data, as no geographical restrictions were made in the search. However, any operational applications that have not been scientifically published and that were not reached by the questionnaire will most likely be missed in this review.

3. Scientific support for operational applications of OS rainfall data

In this section, the results from the literature review based on the collection of references described in section 2 are provided. The section reviews different approaches used for OS rainfall mapping and specifics of using OS rainfall data in subsequent applications. The literature review is made under the general assumption that the data are appropriately quality assured prior to (or in) the application; thus, we do not include work on developing quality assurance algorithms or protocols but refer to dedicated literature on this topic (e.g., Chen et al. 2021; El Hachem et al. 2024; Ośródka et al. 2025). However, as quality assurance is still one of the major challenges with respect to applications of OS rainfall data, it is discussed in section 5.

a. *Rainfall mapping*

1) SINGLE TYPE OF OPPORTUNISTIC SENSOR

Even before the feasibility of CML rainfall retrieval was shown (Messer et al. 2006; Leijnse et al. 2007), methods have been proposed to tomographically reconstruct rainfall fields from the path-averaged information that microwave links provide (Giuli et al. 1991). However, despite that a countrywide study with synthetic CML rainfall data did show the applicability of tomographic reconstruction (Zinevich et al. 2008), simpler methods have been predominantly applied for this task, in particular when larger datasets were used. The first countrywide CML-based rainfall maps were produced in the Netherlands using kriging and considering each CML as a synthetic point observation at the center of its path (Overeem et al. 2013). Similarly, countrywide rainfall maps have been produced and analyzed in Germany (Graf et al. 2020) and for the Czech–German transboundary region (Blettner et al. 2023), using inverse-distance weighting (IDW) instead of kriging. These studies showed that CML-based rainfall maps can perform comparably to gauge-adjusted radar rainfall maps. With CML data being available in real time, given a suitable data acquisition system is in place, rainfall maps can also be produced with only some minutes of delay, as shown for the city of Gothenburg in Sweden (Swedish Meteorological and Hydrological Institute (SMHI) 2025]. Following the successful applications in Europe, the established methods have been transferred to developing countries, where CMLs have an even larger potential due to sparse rain gauge networks. An application covering a large part of Sri Lanka using kriging (Overeem et al. 2021) and a high-resolution application on the city scale in West Africa using IDW (Djibo et al. 2023a) highlight this potential.

Even though most larger-scale applications have used IDW or kriging with a synthetic point representing a CML due to their simplicity and execution speed, method developments for better leveraging the path-averaged rainfall information from CML have continued. One pragmatic solution is to represent the CML rainfall information via several synthetic point observations along the link path and then redistribute the rain-rate values depending on the data from neighboring CML (Goldshtein et al. 2009). This approach can be beneficial in a dense CML network, if small-scale rain cells with spatial extent similar to the CML length exist (Eshel et al. 2017). Tomographic reconstruction (D'Amico et al. 2016) and a stochastic space–time model (Zinevich et al. 2008) have also been applied to small CML datasets. In addition, to account for regional differences in CML density, the optimal grid resolution for CML rainfall field reconstruction has been studied (van de Beek et al. 2020).

It should be emphasized that the potential errors in CML rainfall estimation generally have a larger impact on the quality of reconstructed rainfall maps than the spatial reconstruction process (Rios Gaona et al. 2015). In Fig. 2, an illustration is provided of the rather limited difference between applying IDW and kriging, respectively, when gridding CML data from the Open sharing of high-resolution data from Microwave links, Radar, and Gauges (OpenMRG) dataset (Andersson et al. 2022). Hence, the improvement introduced by sophisticated spatial reconstruction methods can be negligible in real-world applications if CML data quality control (QC) and rainfall estimation are lacking skill. An overview of all studies with rainfall mapping from real CML data is provided in Table 2.

Despite the large increase in PWS in the last few years, there are still only a few studies where only data from PWS

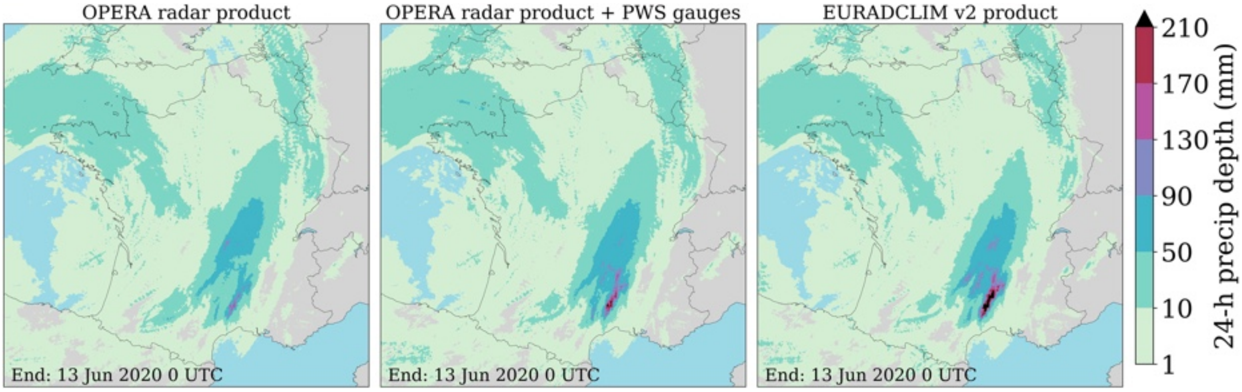

FIG. 3. Map of France with the 24-h radar accumulations from 0000 UTC 12 Jun to 0000 UTC 13 Jun 2020 for the unadjusted OPERA product (with additional nonmeteorological echo removal applied), the same OPERA product merged with 1-h PWS rain gauge (https://www.netatmo.com/en-eu/smart-weather-station#specifications) accumulations, and the same OPERA product merged with disaggregated 1-h official rain gauge accumulations from ECA&D (EURADCLIM). Maps produced with the Python package Cartopy (Met Office 2024) and with Natural Earth (free vector and raster map data © https://naturalearthdata.com).

2) Merged opportunistic and conventional sensors

An initial test on merging of radar and CML data was performed in the early stage of the opportunistic exploitation of CML by Overeem et al. (2012) and is currently under way in several projects from a number of national meteorological services [see section 3a(1)]. Haese et al. (2017) provide hourly rainfall maps where accumulations from German Weather Service rain gauges and CML have been merged over southern Germany. Blettner et al. (2022) employed a random mixing method to generate rainfall maps based on CML and official rain gauge data over Germany for 815 hourly time steps. A showcase of merging radar and CML data on an hourly basis is given in Overeem et al. (2024b). They compared unadjusted, gauge-adjusted, and CML-adjusted rainfall fields for a 3-month period and found an improvement of the resulting rainfall fields evaluated on a daily scale. They argue that the positive impact from the larger density of CML compared to rain gauges exceeds the negative impact from the higher uncertainty in the CML data.

For regions lacking surface rainfall observations, especially low- to middle-income countries in the Global South, merging of CML and satellite products would provide an opportunity to combine the wide coverage of satellites with the accuracy of CML rainfall estimates. To date, only little work has been done in this respect. Kumah et al. (2022) estimate rainfall in the Kenyan Rift Valley by a random forest model that uses geostationary satellite cloud-top properties, where CML data are employed for model training.

Graf et al. (2021) suggest merging radar observations with PWS data, and this prospect has been demonstrated in three peer-reviewed publications (de Baar et al. 2023; Overeem et al. 2024a,b). Overeem et al. (2024a) merge the European Operational Programme for the Exchange of Weather Radar Information (OPERA) radar with 1-h Netatmo PWS accumulations over a large part of Europe for a 1-yr period. The mean daily precipitation underestimation of ∼28% for the unadjusted daily radar accumulations is reduced to ∼3% for the merged radar-PWS dataset, when compared to independent official rain gauges from the European Climate Assessment and Dataset (ECA&D https://www.ecad.eu). Still, severe underestimations are found for several regions, which can partly be attributed to colder temperatures, pointing to solid precipitation not being melted due to the absence of a heating device in the PWS. Dedicated QC of PWS accumulations is shown to be important for outlier removal. This comprises applying part of a neighbor check method (de Vos et al. 2019) and discarding PWS accumulations when they are too large compared to unadjusted radar accumulations.

Performing PWS data quality control and merging by the methodology outlined in Overeem et al. (2024a), Fig. 3 shows an example of radar-PWS merging for France. The unadjusted OPERA radar product clearly underestimates extreme precipitation in France compared to the climatological dataset European Radar Climatology, version 2 (EURADCLIM v2) (Overeem et al. 2024c), which combines the unadjusted OPERA radar product with official rain gauge accumulations from ECA&D. In contrast, the merged radar-PWS dataset agrees much better with EURADCLIM. Most of the official rain gauges in the climatological EURADCLIM product are only available with a long latency. Hence, the example illustrates the potential of (near) real-time PWS rain gauge accumulations for improving radar precipitation products.

Overeem et al. (2024b) merge 1-h Dutch radar with Netatmo PWS accumulations over the Netherlands for a 3-month period. Before merging, the entire QC from de Vos et al. (2019), and again QC with unadjusted radar accumulations, is applied. Daily radar-PWS rainfall maps outperform those based on radar and Royal Netherlands Meteorological Institute (KNMI) automatic rain gauge data when evaluated against the independent KNMI manual rain gauge network. A rather different methodology is presented by de Baar et al. (2023) for the Netherlands and showcased by a 1-h rainfall map. High-fidelity data from automatic rain gauges are combined with low-fidelity crowdsourced rain gauge data from the Weather Observations Website–Netherlands (WOW-NL) network employing unadjusted Dutch radar accumulations as covariate.

Thus, radar-PWS merging shows potential for improving (real time) radar precipitation products due to their much higher network density compared to official rain gauges and their (near) real-time availability. It is recommended to start assessing the potential added value of crowdsourced rain gauge data on the newest available versions of a radar product.

The added value obtained when combining (sparse) official NMHS precipitation observations with (dense) PWS data is demonstrated by, e.g., Bárdossy et al. (2021). They present a study that combines quality-controlled PWS and rain gauge data from the German Weather Service (DWD) using different interpolation methods, such as ordinary kriging and kriging with uncertain data. The latter accounts for the higher uncertainty of the PWS data by reducing their weights in the interpolation (Bárdossy et al. 2021). This interpolation framework was also applied in a Germany-wide study by Graf et al. (2021), where different combinations of rain gauges and OS were analyzed, as well as in a study by Bárdossy et al. (2022), where precipitation estimates of the flood event in the Ahr Valley in 2021 were improved. Finally, Loglisci et al. (2024) present a 12-h rainfall map based on radar, PWS, and official gauge data in Genoa, Italy.

In three peer-reviewed publications, merging of multiple types of OS rainfall data with data from a conventional sensor is investigated. Bianchi et al. (2013) present a data assimilation approach to merge data from one radar with data from 14 rain gauges from institutes and data from 14 CML in Switzerland, obtaining improved rainfall fields compared to pure radar estimates. Graf et al. (2021) merge CML, PWS, and rain gauge data from the German Weather Service, in different combinations, for whole Germany and compare these results to weather radar data. They found that the combinations with PWS lead to an increasing performance for higher spatiotemporal scales. Nielsen et al. (2024) merge radar with 6-h or daily CML and PWS accumulations for a region in Denmark over a 10.5-month period and derived the best performing product when merging all available datasets. They applied the QC from de Vos et al. (2019) to both the CML and PWS data.

b. *Subsequent applications*

1) Rainfall nowcasting

Nowcasting typically involves statistically extrapolating (radar) rainfall maps up to a few hours ahead and is important for early warnings for severe weather. The major challenge in precipitation nowcasting is the requirement to provide forecasts at high temporal and spatial resolution in real time (in practice, within a few to several minutes). This demand places strict limitations on the type and volume of input data that can be utilized, as well as on the complexity of data quality control methods that can be applied. Precipitation estimation models are typically derived from rain gauges, ground-based weather radars, and satellites, sometimes in combination (e.g., Jurczyk et al. 2020; Yu et al. 2020). All of these observations have their advantages, but at the same time, they are subject to many sources of errors and thus require advanced QC (Ośródka et al. 2022; Ośródka and Szturc 2022).

The use of alternative sources of rainfall information like CML, PWS, or SML data is also possible and can bring major improvement to the precipitation field. However, the operational implementation of such data, i.e., real-time quality control and generation of final precipitation fields, can significantly increase the forecast generation time, while too cursory QC will result in little or no added value. Nevertheless, some attempts are being made to include OS rainfall data in operational algorithms.

Using pySTEPS (https://pysteps.github.io/), Imhoff et al. (2020) explore nowcasting based on CML rainfall maps for the Netherlands for 12 summer days. Performance is comparable to radar nowcasts without gauge adjustment, when compared to a common reference of gauge-adjusted radar rainfall maps. The study showed that CML-based nowcasts have a performance that is quite comparable to rainfall nowcasts with weather radar data, especially for high-intensity rainfall. On the other hand, it also points to some limitations due to the fact that CML are not uniformly distributed in the region and do not exist over large bodies of water. Therefore, rainfall estimates are generally more accurate in urban areas due to the denser CML network, compared to rural areas.

As a next step, CML-based rainfall nowcasting is being investigated for a tropical country without radar coverage, Sri Lanka (Overeem et al. 2021). Ultimately, a merged satellite-CML product could be used for nowcasting, combining the large coverage of satellites with the potentially higher accuracy and the often higher spatial or temporal resolution of CML rainfall estimates (Rios Gaona et al. 2017). Some work in this direction has also been reported in Kumah et al. (2022), which focuses on the topic of estimating precipitation in areas without rain gauges based on the random forest algorithm applied to satellite data [Meteosat Second Generation (MSG)] and CML. Good results were achieved in near–real time, indicating that the method is a promising alternative for rainfall estimation.

In Zhang et al. (2023b), an experiment on rainfall field reconstruction and nowcasting was conducted in an urban area based on data from the CML precipitation monitoring network. A 10-min prediction of the rainfall field was achieved using a nowcasting model based on a long short-term memory neural network. The nowcasting model was evaluated for different types of rainfall, and the model proved to perform much better for stratiform and mixed rainfall than for convective rainfall, most likely because of the uneven spatial distribution, short duration, and high spatiotemporal variability of the latter.

Preliminary steps toward operational use of CML data in real time were also taken in Pasierb et al. (2024), where CML from the Opolskie Voivodeship in Poland was tested. The applied QC method, based on the nowcasting rainfall product rain gauge radar satellite estimates (RainGRS) (Jurczyk et al. 2020) for quality control as well as the raw (nongauge adjusted) radar precipitation product for the reconstruction of the rainfall field along the link, showed significant potential

(Pastorek et al. 2023). Furthermore, Pastorek et al. (2023) proved that even rainfall observations at gauges that are located relatively far from the basin (up to 8 km) can be efficient for calibrating WAA models. The highest added value of CML observations was observed during heavy rainfalls. The advantage of combined CML and rain gauge rainfall data for hydrological modeling was also demonstrated by Cazzaniga et al. (2022), who explored the potential of using CML rainfall data in periurban basins with an area of hundreds of square kilometers. Such basins pose a great challenge for modeling since they involve a mix of fast and slow hydrologic responses due to diverse flow paths, ranging from baseflow-dominated areas to those dominated by pipe flow. Their results, which were obtained with a semidistributed hydrological model, indicate that CML-based hydrological simulations generally yield similar model performance compared to conventional data observed at rain gauges, while combining CML rain data with rain gauge data can further enhance model performance (Cazzaniga et al. 2022).

The rather low number of studies dealing with PWS rainfall data in Table 3 suggests that the application of these datasets is lagging behind the development of these networks. This applies to hydrological modeling, as well as to rainfall field generation (section 3a). The reason for the limited application of PWS rainfall data can be attributed to the nature of these datasets: Namely, simulated flows are rather sensitive to the rainfall input (Huang et al. 2019), i.e., to the uncertainties in the rainfall data, as well as to the disposition of the rain gauge network (Arsenault and Brissette 2014; Tetzlaff and Uhlenbrook 2005; Zeng et al. 2018). Uncertainties in rainfall data considerably affect the accuracy of simulated hydrological variables (Tang et al. 2023), and uncertainties in the observations from the PWS can be greater than those in the observations from official meteorological stations (Giazzi et al. 2022).

Also, other attempts to use OS rainfall data were reported in the literature. For example, Croghan et al. (2019) analyzed the correlation between river temperature and CML-based rainfall to predict river temperature surges. However, the selected studies (Table 3) clearly indicate that flood forecasting can become a field in which OS rainfall data can find a broad application. This corroborates the fact that crowdsourced data in general have been frequently used in the field of natural hazards (Nardi et al. 2021). Nevertheless, the selected publications mainly represent investigative studies, which suggest that the field of hydrological modeling with OS rainfall data is still in its infancy, and further efforts are needed to mainstream these applications.

4. RRO of OS rainfall data

The current state with respect to routine operation of OS rainfall data for different applications within the OpenSense community is presented on the basis of the questionnaire described in section 2. Replies to the questionnaire were received from 17 countries, and 13 countries reported that they have experience with using either PWS or CML or both. In the case of nonresponding member countries, the missing information was filled in by personally contacting relevant people within the OpenSense member countries and by searching the literature.

The results of the questionnaire are illustrated in Fig. 4. The main fields of application (currently or planned for the future) of OS rainfall data are the refinement of rainfall fields and assimilation in NWP models as well as other applications including nowcasting, hydrological simulation, and prediction. Rainfall estimates are primarily made from a combination of conventional measurements, such as rainfall gauge (RG) and/or weather radar (WR), and different types of OS sensors. In the majority of countries, operational use is still rare, but preoperational testing is conducted in research projects on limited spatial and temporal scales.

Twelve countries report on the usage of CML data which could be a result of the composition of the OpenSense action with a larger ratio of CML-focused researchers. Data collection by PWS is currently (January 2025) ongoing in seven countries and by CML in four countries. In the remaining countries, only historical PWS and CML datasets are used. This is most likely because finding a business model or a model of collaboration with mobile network operators beyond the horizon of a single demonstration study is more challenging than buying data from a PWS platform operator with an established business model (see further section 5). To date, real-time data streams have been established in only a few countries, and the experience of respondents indicate that, especially in the case of CML, it is challenging, although organizationally rather than technically.

In terms of RRO, the vast majority of respondents estimated the RRO level to be two, i.e., increased experience, e.g., through large-scale validation studies and/or application experiments. A few cases of RRO = 1 (first experiments, small datasets) exist, and RRO = 3 (quasi/operational state) was given only to the use of CML in Germany and the use of PWS in Poland.

In terms of applications, all responding countries used the OS rainfall data for deriving improved observational products, e.g., through validation and/or for densifying existing networks (not shown in Fig. 4). Subsequent applications of CML for hydrological prediction are reported in four countries and of PWS only in Germany. Germany is the only country where CML and PWS were used jointly in a hydrological study. The rainfall nowcasting application using both CML and PWS is reported in Austria and in Sweden using only PWS.

Some of the collected OS rainfall data are openly shared. Špačková et al. (2021) provide 1 year of CML data from one link in Switzerland together with meteorological observations. In the OpenMRG dataset by Andersson et al. (2022), CML data from 364 links in Sweden are shared, together with rain gauge and radar observations during one summer (this dataset is soon to be updated, e.g., with PWS observations). O'Hara et al. (2023) made a 10-yr dataset of PWS observations from the WOW network in the United Kingdom publicly available. Overeem et al. (2024d) describe a dataset covering the Netherlands with ~1800 CML during almost 4 years. In addition, the European Meteorological Network (EUMETNET) (a network of 33 European NMHS) purchased

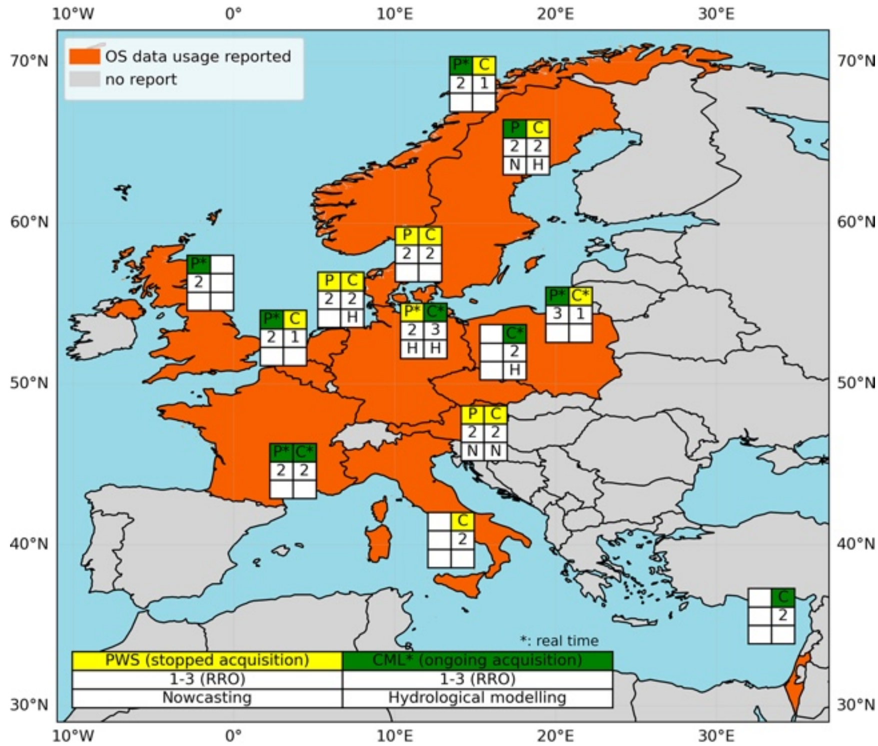

FIG. 4. Results from the questionnaire within the COST Action OpenSense. For each country where OS rainfall data availability was reported, a summary of the national status in terms of data acquisition, self-assessed RRO, and subsequent applications is given. In the national matrices, the top row denotes the OS type (P represents PWS and C represents CML), with green representing an ongoing data stream and yellow representing a terminated stream [the asterisk (*) means that the stream is/was in real time]. The second row contains the RRO and the third row any application performed (N represents nowcasting and H represents hydrological prediction).

PWS datasets from Netatmo and WOW, both covering whole Europe during 2020, and made it available in a "sandbox" to its member countries (Netatmo 2021). To facilitate and improve data sharing and operational usage, an effort to standardize OS rainfall data (and metadata) formats was made by Fencl et al. (2024).

Currently, operational merging of radar and CML data is under way in several projects at a number of NMHS, representing the most advanced state with respect to countrywide operational application of OS rainfall data. In France, Meteo France through the raincell project aims to derive a gauge and CML-adjusted weather radar product that has a very low latency and where CML provides information in areas with poor radar quality (Faure et al. 2024). In the HoWa-PRO project (https://www.wasser.sachsen.de/howa-pro.html), the German Weather Service is building a new operational adjustment system that is capable of including CML (Graf et al. 2024a). They already showed the potential of CML adjustment for an extreme rain event causing heavy flooding over central Europe in July 2021 (Graf et al. 2023). At the Swedish Meteorological and Hydrological Institute, a system for real-time production of gridded high-resolution rainfall including PWS data is being developed (van de Beek and Olsson 2022).

Furthermore, while the focus of this study has been on operational application of OS rainfall data on larger scales (national, regional), it should be emphasized that there are some examples of operational systems and services on a more local scale. Some of these are included in the above literature review, e.g., the local flood forecasting systems in Italy (Ceppi et al. 2023) and Ethiopia (Tedla et al. 2024). There are also nonpublished examples, e.g., Water Board Rijn and Ijssel, the Netherlands, uses PWS rain gauge data for flood forecasting. This type of local initiatives may conceivably initiate a complementary bottom–up movement to spread the applications of OS rainfall data.

5. Remaining challenges and potential solutions

Before CML and PWS data can be used in applications like rainfall mapping, nowcasting, or hydrological prediction, their data have to undergo several processing (CML) or quality control (PWS) steps. Operational applications also require that these steps can be executed in real time. The algorithms need to be tailored to the specific characteristics and error sources of each opportunistic sensor. For CML, a large focus of research in the past 20 years was set on improving processing of raw power level data with the objective to separate raindrop path attenuation from the other signal power losses, which includes, e.g., methods for time series segmentation to dry and rainy periods or for WAA correction. On the one hand, there are now dozens of methods for individual processing steps. On the other hand, the opportunistic nature of CML data, dependency on hardware, or atmospheric conditions still have a significant impact on rainfall estimates, which is difficult to quantify without reliable ground truth. Another aspect adding to the uncertainty of these rainfall estimates is their path-integrated character. Most of the studies consider CML as point observations and apply mapping methods developed for station data. Only a few studies have tried to seize the potential advantage of the path-averaged character of CML observations as listed in section 3a(1).

For PWS, quality control is a postprocessing step and currently an active area of research (e.g., Chen et al. 2021; Tedla et al. 2022; Li et al. 2023; El Hachem et al. 2024). An important aspect prior to the usage is that the literature agrees on an underestimation of rainfall from PWS, especially for heavy rainfall. Bias correction, ideally using nearby dedicated observations, is therefore strongly recommended before using PWS data in applications. Despite all uncertainties, we encourage the use of CML and PWS in practical applications and approaches. However, thorough processing and quality control are essential, as opportunistic data have higher demands compared to professional rainfall observation data. Additionally, as is the case with all applications involving rainfall data, a proper description of the associated uncertainty is required for assessing and quantifying its propagation through subsequent models.

Whereas most work in this review is from Europe, OS rainfall data are often claimed to be particularly attractive in countries with very limited official meteorological networks, e.g., in the Global South. Several investigations have indeed demonstrated how both CML (Doumounia et al. 2014; Overeem et al. 2021; Priebe 2021, 2023; Djibo et al. 2023b; Walraven et al. 2024) and PWS (Mengistie et al. 2024; Tedla et al. 2024) observations have provided an added value in regions otherwise lacking rainfall observations. Applications in different regions are, however, associated with various challenges. Concerning PWS, network density has been shown to substantially depend on the socioeconomic status of the area where PWS are installed (e.g., Brousse et al. 2024). Another challenge is the lack of independent reference observations, preventing efficient bias correction, but the QC has to rely primarily on homogeneity of neighboring PWS observations. Methods for QC relying solely on PWS data have been developed in Europe (e.g., El Hachem et al. 2024), where PWS networks are substantially denser than in low-income countries.

Concerning CML, the selection of appropriate processing methods and parameters still rely on a sufficient amount of reliable reference observations. Additional uncertainties include first that drop size distribution observations specific to climates of tropical and other data-scarce regions are rarely available, which limits the derivation of accurate climate-specific parameter values for the relationship between rain intensity and specific attenuation through scattering computations. Second, 7-GHz CML, commonly used, e.g., in rural parts of Africa, introduces additional challenges. These links have a low sensitivity to rainfall, particularly under light rain conditions. Furthermore, their deployment in long, chained network connections enhances the impact of disruptions. A failure in one connection can affect the entire system, thus reducing data availability. Part of the errors might be identified and possibly also reduced by the comparison of collocated CML (Špačková et al. 2023) or by incorporating additional information from satellite observations in the CML data processing (Graf et al. 2024b). Expert knowledge will always be required when first assessing new CML datasets, as shown in the transnational analysis of two CML datasets by Blettner et al. (2023). Dedicated experiments, where disdrometers, rain gauges, and time-lapse cameras near CML are combined, can be used to investigate CML-specific issues (e.g., WAA) that impact the quality of rainfall estimates (van Leth et al. 2018; Špačková et al. 2021).

Access to CML and PWS data is a fundamental requirement for all subsequent applications. In theory, CML data can be derived and distributed in real time, as demonstrated within the HoWa-PRO project in Germany mentioned above. Similarly, PWS data can be obtained in real time, e.g., via an API with Netatmo or by provision of such a company. In reality, data acquisition is often complicated by a number of factors. One is the dependency on private companies, often associated with a cost outside of individual project-based research and development (R&D) agreements. Here, it must be distinguished between companies dealing directly with meteorological data, including PWS, and companies having another core business, notably telecommunication in the case of CML. In the former case, partnership and contracting is generally straight forward, but in the latter case, the cost of acquiring and processing the raw data often exceeds what, e.g., an NMHS is able to pay. This requires new business models, and for CML, several options are being explored. The Global System for Mobile Communications (GSM) Association has analyzed business case development for the Global South (Priebe 2021, 2023). Their work highlights various use cases implemented in Africa, such as applications for crop insurance companies, and examines the potential roles of mobile network operators (MNOs). But even though such business cases were discussed a lot over the last years, no business model has yet been identified or established. In Europe, there are several ongoing bilateral research collaborations between MNOs and OS researchers; however, the path toward sharing these data for practical application requires sustainable business models and these are yet to be developed.

As part of OpenSense, the Global Microwave Link Data Collection Initiative (GMDI) has been launched to develop recommendations for CML data sharing and transfer mechanisms between MNOs and NMHS (Fencl et al. 2025). For PWS networks, where data are managed by private companies like Netatmo, long-term access free of charge for NMHS is unlikely if not done via policy makers, contrarily to community-driven platforms or cases where voluntary observations are being collected by NMHS networks (e.g., WOW) (e.g., Buyteart et al. 2014; Reges et al. 2016; Tedla et al. 2024).

Besides the costs involved, there is always a risk that private companies change ownership or even go bankrupt, affecting data delivery. Also, the number OS is constantly changing allowing no continuity for NMHS. For CML, there may be both new telecommunication towers constructed or existing towers taken out of service, e.g., when moving over to fiber-based transmission (e.g., Liu et al. 2023). The PWS community is rapidly growing—at the moment—with additional stations being added on a more or less daily basis. Additional complexity arises from people moving and bringing their station, which may require a manual update of the location. Due to these reasons, OS are not able to provide long-term time series for the climatological analysis as professional observations. Another risk is the higher likelihood of gaps than in professional observations, e.g., when devices experience poor connectivity, are being transported, or are put in seasonal storage (e.g., de Vos et al. 2019). Furthermore, the operation (and potential shutdown) of CML is fully subordinated to the needs of the telecommunication network and services provided by network operators. Overall, these risks are conflicting with typical requirements of NMHS who usually want long-term contracts and access to data that should be used in (operational) application frameworks. Although the pioneering studies applying OS rainfall data for hydrological prediction do indicate a clear potential for added value, it should be noted that the associated uncertainties can affect the accuracy of hydrological simulations. Concerning CML data, in addition to uncertainties stemming from WAA (e.g., Pastorek et al. 2023; Stransky et al. 2018), CML rainfall estimates, and consequently simulated flows, can be strongly affected by the CML characteristics and disposition (Pastorek et al. 2019; Turko et al. 2021). Bias in CML rainfall data, which can hinder widespread application in the field of hydrological modeling, can vary over time and rainfall events. Brauer et al. (2016) demonstrated that although their CML rainfall data are on average bias free, they display seasonally varying errors. Cazzaniga et al. (2022) encountered challenges in simulating flows during specific flood events, particularly when CML with coarse quantization (e.g., 1 dB) is used to detect low-intensity rain events.

To take the CML-induced uncertainty into account, Pastorek et al. (2023) proposed coupling the rainfall–runoff models with an error model, the parameters of which can be optimized against a dataset independent from the one used for hydrological model calibration. Generally, uncertainties in rainfall data can be compensated by hydrological model parameterization, to some extent (e.g., Stephens et al. 2022; Wang et al. 2023b; Zeng et al. 2018), but the accuracy of this solution for dynamically changing networks, such as PWS, is questionable. Since model transferability across different rainfall inputs without recalibration is not recommended, another critical issue in the application of OS datasets is their often limited observation period which may be insufficient for calibration, especially in nonurbanized basins. This implies that wider application of OS rainfall data for hydrological prediction is conditioned on steady and stable availability of preprocessed and quality controlled OS rainfall datasets.

Finally, the use of SML has a clear potential for applications such as the ones described in section 3b. While there are equivalent issues with converting attenuation into rainfall intensity as for CML, there are potential advantages including that signal retrieval is not dependent upon telecommunication companies (which facilitates data access) and that the network is stable (e.g., in contrast to CML being replaced by fiber-based transmission). There are a few scientific papers that indicate application potential in the form of rainfall mapping. These include Mercier et al. (2015), who generated SML-based rainfall maps for a few events observed in southern France during the Hydrological Cycle in the Mediterranean Experiment (HyMeX), and Colli et al. (2020), who performed rainfall mapping over an area around Genoa, Italy. From the questionnaire, it was found that SML are currently being explored for applications in, e.g., France and Italy and that companies exploiting SML for rainfall mapping have been recently created, including HD Rain (https://www.hd-rain.com/en/home) and Databourg (https://databourg.com/). We expect to see further progress and increased scientific reporting of these efforts in the coming years.

6. Conclusions

Based on the literature review, the questionnaire, and the discussion, the three questions underlying the study can be addressed as follows.

1) What is the scientific support for operational applications of OS rainfall? There is strong scientific evidence that OS rainfall can provide an added value in high-resolution rainfall mapping, especially when merged with observations from conventional sensors. A potential improvement of subsequent applications—nowcasting and hydrological prediction—is clearly indicated in some studies and less clearly in others, and overall, the number of investigations is still rather low. Most work so far has focused on CML data and less on PWS data, and we found the SML publications to mainly represent a proof-of-concept phase.
2) How technically ready are different countries with respect to operational implementation? All 13 countries that have some experience with OS rainfall data, according to the questionnaire distributed within OpenSense, reported an readiness for routine operation (RRO) level of 2 for at least one type of sensor, i.e., increased experience, e.g., through large-scale validation studies and/or application experiments. Actual operation (RRO = 3) was reported for CML in Germany and PWS in Poland.
3) What challenges remain and how can these be solved? A major scientific challenge is quality assurance (QA)/QC of OS rainfall data and reliable estimation of uncertainty in a final OS rainfall product, particularly in regions with poor reference observations. A major organizational challenge is the acquisition of OS rainfall data, as generally commercial actors need to be involved with associated costs. To solve this, dedicated business models need to be developed, particularly for CML, and efforts in this direction are ongoing. Additional main challenges include the dynamic nature of OS networks, latency limitations across different data sources, and the need for comprehensive (but

fast) processing protocols. More technical research and development is needed to build the required infrastructure.

Concerning future work, it is encouraging that more and more open OS rainfall datasets are being published to facilitate technical developments (section 4). We hope that these efforts will increase the amount of comparative evaluations of OS data against professional observations, not least focusing on extreme rainfall intensities, as well as spawn new initiatives toward improved algorithms for processing, QC/QA, etc. For example, artificial intelligence/machine learning (AI/ML) solutions are conceivably very attractive for merging OS rainfall with conventional observations, considering the complex combination of data of different quality as well as physical dimensions from dynamic networks. To date, only a few studies have employed AI/ML in this context, including, e.g., Niu et al. (2021) for QC/QA of PWS data and Kamtchoum et al. (2022) for nowcasting.

To conclude, we believe that OS rainfall data do have the potential to provide societal benefit in a reasonably near future, by contributing to improved high-resolution rainfall products. These products will, in turn, provide improved reference data for NWP and climate model development, constitute a basis for improved quantitative rainfall estimation and nowcasting, and allow for improved assessment of the extreme rainfall impacts such as landslides, floods, and erosion. In addition to these hydrometeorological benefits, advances in OS rainfall estimation have the potential to provide societal benefits through gaining new understanding and knowledge, e.g., on the character and generation of rainfall extremes. The field of OS rainfall estimation not only provides a promising avenue for cutting-edge multidisciplinary research but also provides an opportunity to enhance existing educational programs and even create new ones. PWS in specific could be beneficial for raising citizens' awareness on rainfall, water resources, and natural hazards in general (Nardi et al. 2021).

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