Crowd-sourced observations for short-range numerical weather prediction: Report from EWGLAM/SRNWP Meeting 2019

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Abstract
Crowd-sourced observations (CSO) offer great potential for numerical weather prediction (NWP). This paper offers a synthesis of progress, challenges and opportunities in this area based on a special session of the EWGLAM Meeting in 2019, concentrating on high-resolution limited-area models (LAMs). Two main application areas of CSO are described: data assimilation and verification. One part of data assimilation developments concentrates on smartphone pressure observations, which represent a large volume of data. However, special care has to be taken about data protection and the quality of observations. In this paper, two examples are presented: the SMAPS experiment from Denmark and the uWx experiment from the United States. Another data assimilation topic is citizen observations with low-cost weather sensors; here an example from Norway is presented using Netatmo stations. The other application area is the use of CSO for model verification. One novel method developed in the United Kingdom is applying social media data to detect severe weather events. This approach is especially important because one future application area of LAM NWP models is impact-oriented warnings.

KEYWORDS
citizen observations, crowd-sourcing, data assimilation, numerical weather prediction, social sensing, verification

1 | INTRODUCTION

In Europe, the landscape of limited-area numerical weather prediction models (LAM NWP) is rather diverse. Currently, six different consortia (ALADIN, COSMO, HIRLAM, LACE, SEECOP, UKMO) are working on the development of these models and their activities are...
coordinated by the C-SRNWP (Coordination on Short Range NWP) module of EUMETNET (European Meteorological Services’ Network). The main forum of this coordination is the yearly EWGLAM/SRNWP Meeting, which brings together model developers from nearly all European National Meteorological Services. The Meeting has been organised since 1979 and currently attracts around 90 model developers from more than 30 countries every year. The 2019 Meeting was held in Sofia, Bulgaria, with a special focus on the application of crowd-sourced observations (CSO) in LAM NWP models. In the context of the Meeting, broad aspects of CSO were considered, ranging from third party and citizen observations, to smartphone pressure data, social media and Internet of Things (IoT). The reason for choosing CSO as a special topic was its emerging potential for several aspects of NWP, including data assimilation and forecast verification. Short-range NWP models (e.g., 1–2 km grids) may greatly benefit from the large amount of available CSO data with high spatial and temporal resolution.

2 | HOW MIGHT CROWD-SOURCED OBSERVATIONS BE USEFUL FOR NUMERICAL WEATHER PREDICTION?

New sources of observations are continuously emerging. These include the rapid proliferation of cheap sensors and digital devices, and high volumes of user-generated data from the Web and social media. Here we loosely term such novel data sources as “crowd-sourced observations” (CSO). Some of these sources have great potential to be used in meteorology and NWP models. Useful observations may come from nonconventional sensors such as vehicles (Anderson et al., 2012), personal weather stations (Madaus and Hakim, 2014; Sobash and Stensrud, 2015; Clark et al., 2018; Gasperoni et al., 2019; Nipen et al., 2020) and smartphones (Madaus and Mass, 2017; McNicholas and Mass, 2018b; Hintz et al., 2019b). Alternatively, “social sensing” derives weather observations from social media content. A common challenge with crowd-sourced data is extracting reliable observations from raw data which may be noisy, irregular, and incomplete. This challenge is balanced by the opportunity of high volumes of data that are relatively cheap to obtain and give high temporal and spatial resolution.

Legal matters and constraints must be considered for most types of crowd-sourced data, especially the General Data Protection Regulation (GDPR) that became law in the European Union in 2018. While GDPR is only law inside the EU, many companies and platforms based outside the EU (notably in the United States) have chosen to follow its guidelines in order to trade within the EU. However, we note that the EU-U.S. Privacy Shield was invalidated by the European court of justice as of July 2020. The lawfulness of processing data often centres on the issues of user privacy and consent. Personal data may only be stored and processed with informed consent, which must be carefully managed; if the intended data usage changes, the data processor would have to ask for consent again. Privacy can be preserved through anonymisation, which reduces the legal challenges of data handling since GDPR does not govern such data. However, anonymisation often requires data minimisation and aggregation/generalisation that can reduce the scientific value of the data significantly.

3 | CROWD-SOURCED OBSERVATIONS AND DATA ASSIMILATION

3.1 | General introduction

All national Met Services are under pressure to make cost savings by spending less on maintaining high-quality observing networks housing standard meteorological instruments. Similarly, they are under pressure to make more accurate and detailed forecasts available more rapidly to their customers. So it is not surprising that dense networks of crowd-sourced observations, with data available relatively cheaply, have become a growing focus for experiments in NWP data assimilation. If the potential benefits are to be realised, we need good evidence that issues such as data acquisition, bias-correction, quality control, and correlated error can be addressed and a worthwhile signal extracted from the new data sources. In pursuit of such evidence, it is attractive to begin with a single, basic, “well understood” meteorological variable like surface pressure, which can now be measured by the ubiquitous smartphone. Two presentations at the meeting dealt with this topic. A third highlighted the potential role of denser networks of a variety of data available from a “citizen scientist” network of weather stations, which are now becoming established in many countries.

3.2 | Measuring pressure using smartphones: The SMAPS experiment

Motivated by severe weather events and new emerging technologies, a framework which collects smartphone pressure observations was developed, to investigate the potential use of such data in NWP. The framework, named Smartphone Pressure System (SMAPS), is installed
as an add-on to existing apps running as a background process (Hintz et al., 2019b). In this way, the data can be collected from many sources and sent to storage at a shared database which ensures that the data processing is kept in the meteorological community and efforts of data collection can be shared between meteorological services. Besides pressure, time and a location, a user identifier, the acceleration, and speed of the device are also stored (based on the findings of McNicholas and Mass, 2018a which presented ways to correct the bias of smartphone pressure observation using a machine learning approach).

During the first year of data collection, more than 60 million observations from 150,000 unique devices were collected from Denmark only. Assuming that this is scalable to the rest of Europe, the potential number of observations is about 6 billion observations per year. From the data, frontal zones and large convective cells could be identified directly. Observations were included in the HARMONIE-AROME NWP model by using 3D Variational Data Assimilation (3D-Var). To enter the assimilation system, observations had first to pass through a screening algorithm described by Hintz et al. (2019b). Results showed a decrease of both root-mean-square error (RMSE) and bias of surface pressure for simulations spanning 2 months.

Data assimilation for high-resolution models is needed to forecast small-scale weather features and to utilise more observations. SMAPS computes the instrument error on each device to make it easier to take into account individual observation errors. At the EWGLAM/WRNWP Meeting, future plans to use this crowd-sourced data in an ensemble now-casting product with frequent analysis and overlapping assimilation windows running with sub-kilometre resolution were presented as a first step towards utilising more observations.

3.3 Measuring pressure using smartphones: Experiments with uWx and IBM

An android app, uWx, was developed to test the utility of crowd-sourced smartphone pressure observations for numerical weather prediction (McNicholas and Mass, 2018a). uWx collected pressure observations every 15-min from several thousand smartphones across the U.S. Pacific Northwest. While uWx demonstrated that smartphone pressures could be retrieved frequently and efficiently, the quality of the observations remained poor. Since smartphone pressure sensors have biases which are systematic (Price et al., 2018; Hintz et al., 2019a), the primary source of uncertainty was attributed to location/elevation errors. This realisation facilitated a machine learning approach to predict and bias-correct smartphone pressure errors, using only data from smartphone sensors and GPS.

A series of ensemble data assimilation experiments examined the impact of smartphone pressure assimilation on hourly cycled forecasts. The experiments spanned a 60-hr period characterised by the passage of a cold front across the U.S. Pacific Northwest. The results revealed that bias-corrected smartphone pressures consistently reduced 1-hr altimeter, temperature, and dew-point forecast error throughout the entire 60-hr period. On average, smartphone pressure assimilation reduced 1-hr forecast error by the same magnitude as the assimilation of in situ Mesonet pressure observations. In contrast, uncorrected smartphone pressure observations generally degraded 1-hr forecasts of pressure and dew point (McNicholas and Mass, 2018b).

In partnership with The Weather Company (IBM), the bias-correction approach developed for uWx was applied to millions of smartphones across the continental United States. To better evaluate these observations, a multiresolution kriging analysis (Nychka et al., 2015) was performed to spatiotemporally interpolate super-obbed smartphone pressures onto a 5-km mesh, every 5 min. These smartphone pressure analyses revealed mesoscale structures such as convective cold pools, frontal bands, and atmospheric gravity waves. A comparison of smartphone pressure analyses with MADIS (METAR +Mesonet) analyses demonstrated the ability of smartphone pressures to capture mesoscale features undetected or poorly resolved by current in situ observing networks, which include private weather stations (Miller et al., 2005). This is exemplified in Figure 1, which shows composite reflectively and altimeter analyses during the passage of a mesoscale convective system (MCS) across the U.S. Upper Midwest. In this case, the magnitude of pressure features associated with the convection was larger in smartphone pressure analyses. The pressure gradient between the meso-high and wake-low, associated with the MCS, was also stronger in smartphone pressure analyses than in MADIS pressure analyses. This result, alongside the uWx experiment, suggests that smartphone pressure observations have the potential to enhance existing surface pressure networks and benefit short-term numerical weather prediction.

3.4 Integrating citizen observations in operational weather forecasts

MET Norway is developing and operating, jointly with the Norwegian Broadcasting Corporation, a web-based platform called YR.no. Recently, low-cost and off-the-shelf home weather station devices like Netatmo form
FIGURE 1  Altimeter analysis produced with MADIS (a) and IBM smartphone (b) pressure observations retrieved during a 5-min window centred at 1225 UTC on September 18, 2018. Composite reflectively with MADIS (c) and smartphone (d) pressure analysis contours overlaid in black. MADIS pressure observations include both METARs and Mesonet observations.

FIGURE 2  Using citizen observations to improve operational weather forecasts. Noncorrected forecast of temperature (left) and analysed (corrected) field (right). Coloured circles are the observations (in °C)
private networks that provide real-time observations. In March 2018, MET Norway introduced the Netatmo observations into the postprocessing of the operational temperature forecasts on Yr for Nordic countries. This was a challenging task due to quality control issues. For example, none of the explored networks (national in situ, Netatmo, radar) was able to show with high accuracy that there is no rain over Oslo and its surrounding area. One needs to combine the different observations to derive a valid weather condition.

The Netatmo network is growing very fast, but the observations it generates need to be subjected to proper quality control (QC). For precipitation analysis, the QC is based on cross-check between temperature and precipitation, adjustment for wind-induced under-catch, check against radar data, check against NWP ensemble, buddy check, check for any holes in the field, and spatial consistency test. For temperature, the QC is based on check against NWP ensemble, buddy check, and spatial consistency test. The analysis uses a two-dimensional optimum interpolation (OI) scheme which takes into account the observations (in situ, radar, Netatmo) and NWP forecasts using maximum radius distance of about 30 km, terrain elevation of about 200 m, land and sea mask, and also incorporates the ensemble covariance structure (e.g., no spread of increment across a front).

Figure 2 (left) presents a forecast temperature field and the observations, where inside the fjord the observations show colder values compared to the forecast ones. Figure 2 (right) shows the analysed fields, where the fjord became colder and the surrounding warmer with agreement to the observations. The QC TITAN (Nipen et al., 2020) is mostly written in R and using some C language while the IO GriPP (Lussana et al., 2019) is coded in C++ with available libraries.

4 USING CROWD-SOURCED OBSERVATIONS FOR VERIFICATION

4.1 Forecast verification using crowd-sourced observations

An opportunity for CSO arises from the move towards impact-based weather forecasting, which focuses on the social/economic impacts of weather (World Meteorological Organisation, 2015; Taylor et al., 2018) and must therefore incorporate such observations into the verification process. For example, an impact-based system will only issue a weather warning if a weather event is both likely to occur and likely to have a major impact on human activity. Systematic observations of impacts are needed to verify/validate impact-based forecasts and models, but such information lies beyond the scope of conventional meteorological observations. Different kinds of CSO can be used to observe social impacts of weather (Spruce et al., 2020). Citizens can provide observations through a designated platform or website, for example, the UK Met Office “Weather Observation Website”1 or the UKSnowMap.2 Alternatively, observations can be derived from unsolicited social media or other sources. A challenge for such “social sensing” methods is to find a robust signal amidst the noise.

4.2 Weather impact monitoring using social media

Social sensing uses large numbers of social media posts to observe real-world events. After a landmark study used Twitter data to detect earthquakes (Sakaki et al., 2010), social sensing has been applied to various weather hazards. One example study used Twitter data to detect and locate floods in England and Wales (Arthur et al., 2018). The methodology involved several stages: data collection, data filtering, location inference, and visualisation. Data collection obtained tweets using a small number of flood-related keywords (“flood,” “flooded,” “flooding”). Filtering removed irrelevant content by rejecting retweets, tweets by automated “bot” accounts (e.g., amateur weather stations linked to Twitter accounts), and tweets not providing immediate flood observations (using machine learning to classify content). Geographic filters were then applied to remove tweets from outside the study area. Location inference was used to estimate locations for the vast majority of tweets which do not carry locations in their metadata. After filtering, very few data are retained; in Arthur et al. (2018) only 79,163 of 17,828,704 (0.4%) of tweets were kept. The cleaned tweets represent the social sensing “observation” and may be visualised (as in Figure 3) or further analysed. Validation using flood observations by the UK Flood Forecasting Centre found that social sensing identified almost all known flood events and a number of previously unknown events (Arthur et al., 2018).

Similar methods have been applied to wildfires (Boulton et al., 2016), airborne pollen (Cowie et al., 2018), and storms (Spruce et al., 2020). Spruce et al. (2020) focused on social impacts of named storms in UK/Ireland, categorising tweet content by impact (damage, disruption, warnings, observations, humour, news) and showing that social media activity tracked storms through time and space, typically with warnings shared in advance and damage/disruption reported during the storm. Sentiment analysis was used to show that storms have a negative emotional impact, greater than that triggered by rainfall or winds alone.
5 | DISCUSSION

As horizontal resolution of NWP models is increasing, more and more observations are needed to produce an adequate initial condition for these models. One candidate to provide large amounts of meteorological observations for NWP models is crowd-sourced observations (CSO), which potentially provide high volumes of data at high spatial and temporal resolution. The 2019 EWGLAM/SRNWP Meeting was focused on the use of CSO in weather modelling, giving the limited-area NWP community an overview on the topic and its challenges.

At the Meeting, presentations showed how CSO can serve LAM NWP models in two main ways: CSO used in data assimilation, and CSO used in forecast verification. In data assimilation, several observation types are being investigated in parallel. Two types of CSO are at a relatively well-developed stage. One is pressure observations from smartphones, while the other is citizen observations from various networks (e.g., Netatmo). These applications were discussed and show great potential. The use of CSO in the verification process was also discussed at the EWGLAM Meeting, with a focus on citizen sensing of weather impacts using social media data. As National Meteorological Services are moving towards impact-based forecasts there is an urgent need to have objective measures from the meteorological impact of severe weather events and CSO can provide valuable information in this respect.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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ENDNOTES

1 WOW: Met Office Weather observation website. Available at: https://wow.metoffice.gov.uk/. Accessed April 2, 2020.
REFERENCES

Anderson, A.R.S., Chapman, M., Drobot, S.D., Tadesse, A., Lambi, B., Wiener, G. and Pisano, P. (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.

Arthur, R., Boulton, C.A., Shotton, H. and Williams, H.T. (2018) Social sensing of floods in the UK. PLoS One, 13, e0189327.

Boulton, C.A., Shotton, H. and Williams, H.T. (2016) Using social media to detect and locate wildfires. Proc. 1st International Workshop on Social Web for Environmental and Ecological Monitoring (SWEEM) at International Conference on Web and Social Media (ICWSM 2016), Cologne, Germany (AAAI).

Clark, M.R., Webb, J.D.C. and Kirk, P.I. (2018) Fine-scale analysis of a severe hailstorm using crowd-sourced and conventional observations. Meteorological Applications, 25, 472–492.

Cowie, S., Arthur, R. and Williams, H.T. (2018) @ choo: Tracking pollen and hayfever in the UK using social media. Sensors, 18, 4434.

Gasperoni, N., Wang, X., Brewster, K.A. and Carr, F.H. (2019) Assessing impacts of the high-frequency assimilation of surface observations for the forecast of convection initiation on 3 April 2014 within the Dallas–Fort worth test bed. Monthly Weather Review, 146, 3845–3872.

Hintz, K.S., O’Boyle, K., Dance, S.L., Al-Ali, S., Anspier, I., Blaauboer, D., Clark, M., Cress, A., Dahoui, M., Darcy, R., Hyrkkanen, J., Isaksen, L., Kaas, E., Korsholm, U.S., Lavanant, M., Le Bloa, G., Mallet, E., McNicholas, C., Onvlee-Hooimeijer, J., Sass, B., Siirand, V., Vedel, H., Waller, J.A. and Yang, X. (2019a) Collecting and utilising crowdsourced data for numerical weather prediction: Propositions from the meeting held in Copenhagen, 4–5 December 2018. Atmospheric Science Letters, 20, e921.

Hintz, K.S., Vedel, H. and Kaas, E. (2019b) Collecting and processing of barometric data from smartphones for potential use in numerical weather prediction data assimilation. Meteorological Applications, 26, 733–746.

Lussana, C., Seierstad, I.A., Nipen, T.N. and Cantarello, L. (2019) Spatial interpolation of two-meter temperature over Norway based on the combination of numerical weather prediction ensembles and in-situ observations. Quarterly Journal of the Royal Meteorological Society, 145, 3626–3643.

Madaus, L., G. and Hakim, C.M. (2014) Utility of dense pressure observations for improving mesoscale analyses and forecasts. Monthly Weather Review, 142, 2398–2413.

Madaus, L. and Mass, C. (2017) Evaluating smartphone pressure observations for mesoscale analyses and forecasts. Weather and Forecasting, 32, 511–531.

McNicholas, C. and Mass, C. (2018b) Impacts of assimilating smartphone pressure observations on forecast skill during two case studies in the pacific northwest. Weather and Forecasting, 35, 1375–1396.

McNicholas, C. and Mass, C. (2018a) Smartphone pressure collection and bias correction using machine learning. Journal of Atmospheric and Oceanic Technology, 35, 523–540.

Miller, P., Barth, M. and Benjamin, L. (2005) An update on madis observation ingest, integration, quality control and distribution capabilities. In: 21st International Conference on Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology. San Diego, CA: American Meteorological Society, Available at: https://ams.confex.com/ams/Annual2005/techprogram/paper_86703.htm.

Nipen, T.N., Seierstad, I.A., Lussana, C., Kristiansen, J. and Hov, O. (2020) Adopting citizen observations in operational weather prediction. Bulletin of the American Meteorological Society, 101, E43–E57.

Nychka, D., Bandyopadhyay, S., Hammerling, D., Lindgren, F. and Sain, S. (2015) A multiresolution gaussian process model for the analysis of large spatial datasets. Journal of Computational and Graphical Statistics, 24, 579–599. https://doi.org/10.1080/10618600.2014.914946.

Price, C., Maor, R. and Shachaf, H. (2018) Using smartphones for monitoring atmospheric tides. Journal of Atmospheric and Solar-Terrestrial Physics, 174, 1–4.

Sakaki, T., Okazaki, M. and Matsuo, Y. (2010) Earthquake shakes twitter users: real-time event detection by social sensors. In: Proceedings of the 19th International Conference on World Wide Web. New York, NY: Association for Computing Machinery, pp. 851–860.

Sobash, R. and Stensrud, D. (2015) Assimilating surface mesonet observations with the enkf to improve ensemble forecasts of convection initiation on 29 May 2012. Monthly Weather Review, 143, 3700–3725.

Spruce, M., Arthur, R. and Williams, H. (2020) Using social media to measure impacts of named storm events in the United Kingdom and Ireland. Meteorological Applications, 27, e1887.

Taylor, A.L., Kox, T. and Johnston, D. (2018) Communicating high impact weather: improving warnings and decision making processes. International Journal of Disaster Risk Reduction, 30, 1–4.

World Meteorological Organisation. (2015) WMO guidelines on multi-hazard impact-based forecast and warning services. Geneva, Switzerland: WMO (Technical report).

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